University of Kentucky
UKnowledge

Theses and Dissertations--Educational, School, and Counseling Psychology

Educational, School, and Counseling Psychology

2014

MEASURING UNDERGRADUATE STUDENTS' ENGINEERING SELF-EFFICACY: A SCALE VALIDATION STUDY

Natasha Johanna A. Mamaril
University of Kentucky, tasha1214@gmail.com

Right click to open a feedback form in a new tab to let us know how this document benefits you.

Recommended Citation
Mamaril, Natasha Johanna A., "MEASURING UNDERGRADUATE STUDENTS' ENGINEERING SELF-EFFICACY: A SCALE VALIDATION STUDY" (2014). *Theses and Dissertations--Educational, School, and Counseling Psychology*. 19.
https://uknowledge.uky.edu/edp_etds/19

This Doctoral Dissertation is brought to you for free and open access by the Educational, School, and Counseling Psychology at UKnowledge. It has been accepted for inclusion in Theses and Dissertations--Educational, School, and Counseling Psychology by an authorized administrator of UKnowledge. For more information, please contact UKnowledge@lsv.uky.edu.

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Natasha Johanna A. Mamaril, Student

Dr. Ellen L. Usher, Major Professor

Dr. Kenneth M. Tyler, Director of Graduate Studies

MEASURING UNDERGRADUATE STUDENTS' ENGINEERING SELF-EFFICACY: A SCALE VALIDATION STUDY

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Education
at the University of Kentucky

By

Natasha Johanna A. Mamaril

Lexington, Kentucky

Chair: Dr. Ellen L. Usher, Associate Professor of Educational Psychology

Lexington, Kentucky

2014

Copyright © Natasha Johanna A. Mamaril 2014

ABSTRACT OF DISSERTATION

MEASURING UNDERGRADUATE STUDENTS' ENGINEERING SELF-EFFICACY: A SCALE VALIDATION STUDY

The purpose of this study was to develop and evaluate engineering self-efficacy measures for undergraduate students (N = 321) and to examine whether students' engineering self-efficacy differed by gender, year level, and major. The relationships between engineering self-efficacy and academic achievement and intent to persist in engineering were also investigated. Data from engineering students from two southeastern universities were collected in spring 2013. Exploratory factor analyses resulted in a unidimensional general engineering self-efficacy scale and a three-factor (i.e., research skills, tinkering skills, and engineering design) engineering skills self-efficacy scale. Multivariate analyses of variance revealed that self-efficacy did not differ by gender or year level. Students in different engineering sub disciplines reported different levels of tinkering self-efficacy. Multiple regression analysis showed that engineering self-efficacy measures predicted academic achievement outcomes but not intent to persist in engineering. Engineering self-efficacy significantly contributed to the prediction of achievement after controlling for prior achievement.

Research funded by the National Science Foundation, EEC Award #1240328.

KEYWORDS: General Engineering Self-Efficacy, Engineering Skills Self-Efficacy, Achievement, Intent to Persist, Undergraduate Engineering Students

Natasha Johanna A. Mamaril
Student's Signature

6/10/2014
Date

MEASURING UNDERGRADUATE STUDENTS' ENGINEERING SELF-EFFICACY:
A SCALE VALIDATION STUDY

By

Natasha Johanna A. Mamaril

Dr. Ellen L. Usher
Director of Dissertation

Dr. Kenneth M. Tyler
Director of Graduate Studies

6/16/2014
Date

For Papa

You inspired me to be an engineer

Acknowledgments

I would like to express my sincerest gratitude to the members of my committee for providing insights and direction throughout the dissertation process. First, I want to thank Dr. Usher, my dissertation adviser, for always challenging me to do better and for her patience and guidance as I pursued my graduate degree. To Dr. Danner, Dr. Bradley, Dr. Rostosky, and Dr. Kennedy, thank you for your feedback, comments, and encouragement. In addition, I am thankful to Dr. Usher and Dr. Kennedy for the opportunity to work on the National Science Foundation - Research Initiation Grant in Engineering Education project that helped fund my dissertation study.

I am also thankful for the support of family and friends who have been there to pray for me, cheer me on, and help me in any way they could. I am blessed to have you all in my life. This dissertation would not have been completed without the patience, love, and understanding of my husband, Cezar Brian, and my daughter, Caitlin. I hope you are as proud of me as I am proud of both of you.

Last, I would like to acknowledge that all I have comes from the Lord. I am grateful for the opportunities that He has provided and for the many blessings He has given. Through the tough times, the Lord is my rock and my salvation.

Table of Contents

List of Tables

Chapter 1: Introduction

The National Science Board (2012) reported that about 4% of all bachelor's degrees awarded in the United States in 2008 and in 2009 were in engineering. The United States earned only 10% of the five million undergraduate degrees awarded in science and engineering worldwide in 2008 compared to China, which had 23%, and the European Union, which earned about 19%. In 2011, the American Society of Engineering Education reported that the number of degrees awarded at all degree levels grew from the past year. Yet, the number of engineering degrees awarded to American students at all degree levels decreased by 4% (Yoder, 2011). To maintain its global competitiveness, the United States must be able to supply the market demand for engineers. Engineering educators in the United States are challenged with addressing the decline in numbers of engineering graduates.

Engineering students' academic success has been linked to pre-college achievement scores such as those on the mathematics section of the Scholastic Assessment Test (SAT) and the American College Testing (ACT). Studies have shown that SAT mathematics scores predict first term grade point average (GPA; Besterfield-Sacre, Atman, & Shuman, 1997) and college GPA (French, Immekus, & Oakes, 2005), whereas ACT mathematics scores predict passing grades in freshman courses (Veenstra & Herrin, 2006). Clearly, having quantitative skills upon entering engineering programs helps prepare students for the rigors of the engineering curriculum and will likely help them get through their first year of engineering courses. However, having these skills alone does not ensure that students will be motivated to complete their engineering degrees.

Individuals' success in engineering lies not only in their achievement and ability but also in their social cognition and self-beliefs (Bandura, 1986; Betz & Hackett, 1981; Hutchison, Follman, Sumpter, & Bodner, 2006; Lent Brown, & Hackett, 1994). Students' self-efficacy has been identified as a significant factor contributing to their persistence and achievement (Schunk & Pajares, 2002). Self-efficacy refers to "the beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). Such beliefs influence the choices people make, the effort they put into a task, their perseverance when difficulties arise, their resilience to adversity, and their coping skills. Bandura (1997) contended that self-efficacy is not about the number of skills people have but what people believe they can do with these skills under a variety of circumstances. For undergraduate engineering students to function most effectively in their degree programs, they must have the required skills and competencies. They must also have the *belief* that they are able to perform these skills.

Self-efficacy is a significant factor contributing to students' persistence and academic achievement. A meta-analysis of self-efficacy studies has shown that self-efficacy accounted for an average of 14% of the variance in students' academic performance and approximately 12% of the variance in their academic persistence (Multon, Brown, & Lent, 1991). Although none of the studies included in this meta-analysis featured self-efficacy in the domain of engineering, the results provide support that self-efficacy is a variable worth exploring in motivation studies in engineering. Researchers have explored self-efficacy in engineering by measuring self-efficacy in engineering-related domains such as mathematics and science. Even though mathematics and science are part of the engineering curriculum, researchers in engineering education emphasize that there is a growing need to study engineering in its distinct context to capture unique experiences specific to this domain.

Researchers have recommended that engineering educators commit to identifying the skills that are important to practicing engineers and to incorporating strategies that enhance confidence in performing these skills (Ponton, Edmister, Ukeiley, & Seiner, 2001). On a general level, engineering students should then possess the knowledge of fundamental engineering principles and laws and should be able to apply this knowledge and to convert theory into practice. In addition, engineering students should also have intellectual skills such as logical thinking, problem solving skills, and communication skills (Nguyen, 1998).

Engineering educators have also identified engineering-specific skills that engineering students should possess to become engineers. For example, Towle, Mann, Kinsey, O'Brien, Bauer, and Champoux (2005) suggested that spatial ability, the ability to correctly visualize three-dimensional objects when they are represented in two dimensions, is an essential skill for engineers. Engineering design skill, the ability to design a system or component to meet an identified need, is another important skill for engineering students to have, especially in preparing students for industrial demands (Carberry, Lee, & Ohland, 2010; Schubert, Jacobitz, & Kim, 2012). Researchers have also specified tinkering skills and technical skills, which are useful in creating and modifying products, as crucial for engineers (Baker, Krause, Yasar, Roberts, & Robinson-Kurpius, 2007). Tinkering skills involve engaging in manual activities such as disassembling a vacuum cleaner, whereas technical skills refer to applying technical academic subject matter. Given that these skills are deemed important to a practicing engineer, there is value in assessing students' beliefs that they are able to perform these skills.

Statement of the Problem

Although the existing research indicates a strong relationship between self-efficacy and academic achievement, there is a need to craft an engineering self-efficacy scale that can tap the multifaceted nature of self-efficacy in the engineering domain. The domain of engineering included a variety of disciplines such as chemical engineering, civil engineering, electrical engineering, and mechanical engineering. The assumption is that engineering skills common to these disciplines exist (Nguyen, 1998). In fact, the Accreditation Board for Engineering and Technology (ABET) has established a set of abilities that graduates of undergraduate engineering programs should have. Engineering students should then possess these abilities and have the belief that they can use their abilities in various circumstances (Bandura, 1997).

General self-efficacy scales have been employed to measure engineering self-efficacy. A common misconception is that "general efficacy beliefs spawn specific efficacy beliefs" (Bandura, 1997, p. 41). Bandura (1986) cautioned that general self-efficacy assessments are omnibus measures that create problems of predictive relevance. They may have little or no relation to self-efficacy in particular activity domains or even to behavior (Bandura, 1997). Even at the general level, self-efficacy measures should be relevant to the domain of functioning that is the object of interest (Bandura, 2006).

Current measures of self-efficacy in engineering have included activities in engineering-related domains, particularly mathematics and science. Pajares (1996) emphasized that self-efficacy should be assessed at the optimal level of specificity that corresponds to the task being assessed and the domain of functioning being analyzed. To assess college students' engineering self-efficacy, the self-efficacy measure should provide clear activities or tasks in the domain of engineering. Students may then generate judgments about their capabilities with specific situations in mind. Self-efficacy judgments should be consistent with and tailored to the domain of engineering and to engineering tasks to achieve explanatory and predictive power (Pajares, 1996). Thus, a better measure of engineering self-efficacy is needed to adequately assess engineering students' beliefs in their capabilities to perform tasks in their engineering coursework and their future roles as engineers.

Purpose of the Study

The aims of this dissertation study are: (a) to develop engineering self-efficacy scales for college students and to determine the content, construct, concurrent, and predictive validity of the instruments; (b) to determine the reliability of the scale when used with undergraduate engineering students; and (c) to add to the current body of literature on self-efficacy in the field of engineering by investigating the relationships among engineering self-efficacy, achievement, and other motivation constructs.

Significance of the Study

My hope is that results of this study will provide engineering educators and researchers with a psychometrically sound instrument that reflects the multidimensionality of engineering self-efficacy. I will also demonstrate the utility of engineering self-efficacy in predicting engineering students' performance in their programs. I expect the results of this investigation to show the predictive power of a general engineering self-efficacy measure and a task-specific self-efficacy measure in relation to engineering students' achievement and intent to persist in engineering.

Success in engineering is essential to the development of the engineering workforce needed to support the industries in the United States. Engineering educators have identified the skills and knowledge that future engineers should possess. Although some researchers (e.g., Ponton, 2002; Ponton et al., 2001) have emphasized the need to develop engineering students' self-efficacy, engineering educators have yet to understand the role of self-efficacy in students' academic and professional performances. The self-efficacy measures developed from this study may be useful in predicting students' persistence in engineering programs and their intent to practice engineering.

Copyright © Natasha Johanna A. Mamaril 2014

Chapter 2: Review of the Literature

The overarching objective of this study is to investigate the relationships among engineering motivation, academic achievement, and the intent to persist in engineering programs. In this dissertation study, I focus on the academic motivation of undergraduate engineering students, particularly their self-efficacy, a central construct of social cognitive theory. To properly situate this study, I provide an overview of social cognitive theory, which serves as the guiding theoretical framework. I then describe self-efficacy and its sources, and review how self-efficacy has been examined in the domain of engineering.

Overview of Social Cognitive Theory

Social cognitive theory (SCT) is based on the view that personal factors (in the form of cognition, biological, and affective states), behavioral factors, and environmental factors dynamically interact in a process of triadic reciprocality (Bandura, 1986, 1997). These factors are interconnected and affect one another. For example, engineering students who are confident in their laboratory skills (personal factor) may perform well in laboratory activities (behavioral factor) and be invited by engineering faculty (environmental factor) to conduct research with them. Bandura (1997) has asserted that most motivation for human action stems from the central belief in the power of one's actions to bring about results. It is for this reason that people's behaviors can often be better predicted by the *beliefs* they hold about their capabilities than by what they have actually accomplished.

Self-Efficacy

Self-efficacy refers to the beliefs that people have in their capabilities to perform life's tasks (Bandura, 1997). These beliefs help determine the amount of effort exerted in an activity and people's persistence and resilience in the face of adversity (Pajares, 1996). If people believe they can achieve a certain goal, such as obtaining an engineering degree, then they will likely work towards that goal by studying and meeting the course requirements. Students who believe in their abilities to perform certain engineering tasks (e.g., design a building) are typically more motivated to complete those tasks (Bandura, 1997).

Bandura (1997) hypothesized that individuals' self-efficacy is shaped by their interpretation of information from four sources, namely, mastery experience, vicarious experience, social persuasions, and physiological states. Mastery experience may be defined as the interpreted result of one's own performances. Successes are usually interpreted with a sense of accomplishment that raises one's self-efficacy. Students who have previous success in an academic task, such as problem solving, tend to believe they are capable of performing similar tasks in the future. Vicarious experience takes place as individuals observe models and learn from their experiences (Bandura, 1986). People compare themselves to others and evaluate their own capabilities in relation to models' successes and failures (Bandura, 1997). When students see their peers solve a problem in a certain way, they may come to believe that they could solve the problem, too.

Social persuasion often takes the form of verbal judgments that students receive from other people. Whether in the form of an encouragement or otherwise, social persuasions can strengthen or weaken people's self-efficacy (Schunk & Pajares, 2005).

A professor's praise of a student's design of a contraption may enhance the student's self-efficacy compared to a fellow student's positive comments about the design. Physiological states arise as students experience stress or fear as they perform or think about performing a given task. Bandura (1997) noted that affective and physiological reactions to a task can signal possible success or failure. Strong negative thoughts and fears about one's capabilities can lower self-efficacy perceptions and lead to poor task performance. Together, these four sources of self-efficacy inform individuals of their capabilities. Bandura (1997) pointed out that efficacy beliefs are individuals' interpretations of the information conveyed enactively, vicariously, socially, and physiologically.

Self-Efficacy in Engineering

In this section, I provide a review of selected literature pertaining to undergraduate students' self-efficacy in the domain of engineering. I discuss how engineering self-efficacy has been measured by critically examining the measures used based on Bandura's (2006) guide for constructing self-efficacy scales. I also present findings from studies that have focused on the self-efficacy of engineering students and its relation to gender, year-level classification, and achievement outcomes. I close by briefly discussing other motivation constructs that have been studied together with engineering self-efficacy.

The articles for the literature review were found by conducting searches on online databases (e.g., EBSCOhost, JSTOR, PsycINFO, Web of Science) using the following key words in different combinations: *engineering, engineer, motivation, retention, attrition, persistence, social cognitive theory, self-efficacy, beliefs, and confidence.* I also found articles relevant to my study through the references cited in the articles I came across. I included published articles starting from 1984, because this was the year the first study linking self-efficacy to engineering students was conducted (i.e., Lent, Brown, & Larkin, 1984). I reviewed the studies' key findings and examined the methods used in each study, taking note of the instruments used in quantitative studies (see Table 1). As I am interested in the engineering self-efficacy of college students, I excluded studies focused on K-12 students, graduate students, and practicing engineers.

Measuring Engineering Self-Efficacy

Researchers seem to agree on a conceptual definition of engineering self-efficacy but variations exist in the ways they have measured self-efficacy. Self-efficacy items either concentrate on overall performance levels or on specific facets of task performance. Investigators have assessed engineering self-efficacy in three ways. Some have used omnibus measures of self-efficacy. Others have adapted general measures to the engineering domain. A few investigators have taken a step further by creating self-efficacy measures for specific engineering skills. The use of different assessments to examine engineering self-efficacy and its relation to particular outcomes may render comparability of the findings unclear.

General self-efficacy measures. Some researchers have used general self-efficacy measures to assess engineering self-efficacy (e.g., Dunlap, 2005; Vogt, Hocevar, & Hagedorn, 2007). These general self-efficacy measures are designed to measure

Table 1

Studies Included in the Review of Engineering Self-Efficacy

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Lent, Brown, & Larkin (1984)	42 students who participated in 10-week career -planning course on science and engineering fields	Self-efficacy (SE) preliminary scholastic aptitude test scores, high school ranks, and college grades	Self-efficacy to fulfill educational requirements and job duties of a variety of technical/scientific occupations	Students reporting high SE for educational requirements generally achieved higher grades and persisted longer in technical/scientific majors over the following year than those with low SE. SE was also moderately correlated with predictors of academic aptitude and achievement.
Lent, Brown, & Larkin (1986)	105 undergraduate students who participated in career planning course	Self-efficacy, grades, persistence, perceived career options	Educational requirements scale (Lent et al., 1984) Self-Efficacy for Technical/Scientific Fields based on Betz and Hackett (1981)	Hierarchical regression analysis indicated that SE contributed significant unique variance to the prediction of grades, persistence, and range of perceived career options in technical/scientific fields.
Lent, Brown, Schmidt, Brenner, Lyons, & Treistman (2003)	328 students in an introductory engineering course	Self-efficacy, coping efficacy, outcome expectations, interests, academic goals, environmental supports and barriers	Self-efficacy for Technical/Scientific Fields (Lent et al., 1984) - modified by having participants indicate their confidence that they could complete each of 10 engineering majors with an overall grade point of average of B or better.	Findings indicate good support for a model portraying contextual supports and barriers linked to choice goals and actions (persistence in engineering) indirectly, through self-efficacy rather than directly as posited by social cognitive career theory (SCCT).
Dunlap (2005)	31 students in the capstone course in software engineering	Self-efficacy, sources of SE, final grades	Guided journal General Perceived Self-Efficacy Scale (Jerusalem & Schwarzer, 1992)	Problem-based learning's collaborative process provides explicit feedback to students about their performance, serving as a source of efficacy information that enhances SE development. Through authentic activities, students have an opportunity to practice applying knowledge and skills to new and novel problems and successfully working through these activities increases their performance accomplishments.

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Lent, Brown, Steven, et al. (2005)	487 students in introductory courses	Academic interests, goals, self-efficacy, outcome expectations, environmental supports and barriers, gender university type	Self-efficacy for academic milestones (Lent et al., 1986) Barrier-coping self-efficacy (Lent et al., 2001)	SCCT-based model of interest and choice goals produced good fit to the data across gender and university type. SE appeared to be primary predictor of goals. Supports and barriers jointly predicted SE.
Towle, Mann, Kinsey, O'Brien, Bauer, & Champoux (2005)	219 engineering and physical sciences students	Self-efficacy, spatial ability	Purdue Spatial Visualization Test (PSVT) Self-efficacy on spatial tasks	Engineering students' SE was directly correlated to spatial ability. No difference in self-efficacy among men and women, however, men scored higher than women on the PSVT.
Hutchison, Follman, Sumpter, & Bodner (2006)	1387 first-year students enrolled in ENGR 106 (Problem-Solving and Computer Tools)	Sources of SE, self-efficacy	SE for Academic Milestones (Lent et al., 1986) Academic Efficacy Scale (Midgley et al., 1998) Students were also asked to describe factors on which their confidence rating was based on.	Nine categories emerged from the classification of factors affecting the confidence of students to succeed in ENGR 106: understanding or learning of material, drive or motivation toward success, teaming issues, computing abilities, the availability of help and ability to access it, issues surrounding doing assignments, student problem-solving abilities, enjoyment, interest, and satisfaction associated with the course and its materials, and grades earned in the course. Drive and motivation, understanding of material, and computing abilities as most influential.
Lent, Schmidt, & Schmidt (2006)	Phase 1: 165 students Phase 2: 312 students Students were enrolled in an engineering design course	Collective efficacy, team cohesion self-efficacy, team ratings	Collective efficacy Cohesion subscale (Group Environment Scale; Moos, 1986) Self-efficacy Team performance	Consistent with social cognitive theory, collective efficacy was a stronger predictor of team performance than team members' perceptions of their self-efficacy

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Marra & Bogue (2006)	164 undergraduate female engineering students at 5 universities	Self-efficacy, institution, year-level, ethnicity	Longitudinal Assessment of Engineering Self-Efficacy (LAESE)	Longitudinal significant increases from time1 to time 2 were found for engineering efficacy, coping SE, and math outcomes efficacy. Significant main effect for ethnicity on inclusion subscale. No significant differences found by institution or by year-level.
Baker & Krause (2007)	71 members of ASEE 24 engineering students in a design course 6 engineering faculty		Asked participants to list characteristics of someone with good tinkering skills and of someone with good technical skills	Differences between the characteristics associated with tinkering and technical activities and the ABET criterion 3 a-k learning outcomes suggest that ABET criteria may need to be reviewed in the light of changes in the profession in the innovation-driven global economy.
Baker, Krause, Purzer, Roberts, & Robinson-Kurpius (2007)	5 females 4 males enrolled in a graduate level DET course	Tinkering self-efficacy, technical self-efficacy, societal relevance of engineering	Reflection papers Self-efficacy assessment Informal unstructured classroom observations, three focus group transcripts	Tinkering self-efficacy and technical self-efficacy are malleable and can be improved in women who are provided with the appropriate educational experiences. Study documents the kinds of educational experiences that are most likely to bring about changes in these self-efficacies and also an understanding of the societal relevance of engineering.
Hutchison, Follman, & Bodner (2007)	9 (5 women, 4 men) 2nd year students enrolled in CHE 205 (Chemical Engineering Calculations)	Sources of SE	Semi-structured, open-ended interview protocol	Adaptation to college life and experience with discipline-specific coursework influence engineering students' self-efficacy. Grade-based social comparisons made by 1st year students were rarely discussed by 2nd year students. Students' SE are directly influenced by their learning environment and students appear to place significant importance on mastery experiences.

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Lent, Singley, Sheu, Schmidt, & Schmidt (2007)	153 engineering students (124 men, 21 women, 8 unknown) 74% freshmen 20% sophomores	Self-efficacy, outcome expectations, environmental support, perceived goal progress, academic satisfaction	SE for academic milestones Lent, Brown, et al. (2005)	Structural equation modeling analyses indicated that the social-cognitive model fit the data well overall and that each of the predictors, except for outcome expectations, explained unique variation in students' academic satisfaction.
Vogt, Hocevar, & Hagedorn (2007)	714 students across 4 universities (409 males, 304 females); 89 seniors, 116 juniors, 165 sophomores, 281 freshmen	Environment (discrimination and academic self-confidence) Self (academic self-confidence and self-efficacy) Behavior (help-seeking, peer learning, effort, and critical thinking)	Discriminations scale (Seymour & Hewitt, 1997) Academic integration scale (Santiago & Einarson, 1998) Academic self-confidence subscale from Cooperative Institutional Research Program (CIRP) scale (Astin & Sax, 1994) Self-efficacy items from Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991) Task-specific self-efficacy scale (O'Neil and Herl, 1998) Help seeking, peer learning, effort, and critical thinking items from MSLQ	Findings successfully confirmed Bandura's triadic reciprocality model in showing the effects of classroom environment on students' performance. Results corroborate body of evidence where females reported lower engineering self-efficacy and lower levels of critical thinking. They also reported greater perceived gender discrimination than the male subsample did.
Baker, Krause, & Purzer (2008)	84 freshman students in engineering design class	Tinkering self-efficacy, technical self-efficacy	Tinkering scale Technical scale	Students had moderate self-efficacy in terms of technical skills. Technical Scale reliability coefficient = 0.80; tinkering scale reliability coefficient = 0.87 Three clear factors for technical scale, accounting for 41% of the variance: technical knowledge, understanding theory and models, and systems and how things work. Three clear factors for tinkering scale, accounting for 44% of variance: knowledge and experience, creativity and curiosity, and knowledge and skills.

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Hutchison-Green, Follman, & Bodner, (2008)	12 first-year engineering students	Sources of SE, engineering SE	Semi-structured, open-ended interview protocol SE for Academic milestones (Lent, Brown, & Larkin, 1986) Academic Efficacy Scale (Midgley et al., 1998)	Results demonstrate the susceptibility of first-year engineering students' self-efficacy beliefs to the influence of performance comparisons based on the speed with which students were able to perform various tasks, the degree of contribution they were able to achieve when working with others, how much material they had mastered, and their grades. Gender differences were also identified in the way in which men and women were influenced by these experiences.
Kinsey, Towle, O'Brien, & Bauer (2008)	497 students from various engineering disciplines and undeclared students	Spatial ability, self-efficacy	Purdue Spatial Visualization Test (PSVT) Self-efficacy on spatial tasks	Students' perception of their spatial ability is significantly correlated with how well they perform on the PSVT. Males performed better on the PSVT questions than females but the SE scores reported by both genders were statistically equivalent.
Lent, Sheu, Singley, Schmidt, Schmidt, & Gloster (2008)	209 students taking beginning level engineering courses (166 men, 37 women, 6 unknown)	Self-efficacy, outcome expectations, interests, goals	SE for academic milestones (Lent, Brown, et al., 2005) Barrier-coping self-efficacy	Though findings are consistent with a causal role for self-efficacy, they cannot conclusively prove such a role. SCCT can be used as an explanatory framework on the role of self-efficacy relative to interest and choice processes.
Concannon & Barrow (2009)	519 undergraduate engineering students	Engineering SE, year level, ethnicity, transfer status	Modified subscales of the LAESE	No significant differences in mean engineering SE scores were found by gender, ethnicity, and transfer status. Significant interactions between gender and the subscales, ethnicity and subscales, and transfer status and subscales were found. Significant differences in mean engineering SE scores were found among years students had been enrolled in the program.

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Marra, Rodgers, Shen, & Bogue (2009)	196 undergraduate engineering students in 5 institutions	Career expectations, engineering SE, feelings of inclusion, coping self-efficacy, math expectations	LAESE	Women showed positive progress on some self-efficacy and related subscales and a significant decrease on feelings of inclusion from the 1st to 2nd measurement period. Results also suggest a relationship between ethnicity and feelings of inclusion.
Carberry, Lee, & Ohland. (2010)	202 respondents: 12 engineering professors, 7 engineering education graduate students 28 engineering graduate students 60 engineering undergraduate students 32 non-engineers with science background 37 non-engineers without science backgrounds	Engineering design SE, engineering experience, motivation, expectancy, anxiety	Developed 36-item instrument for engineering design SE	Instrument has been validated as a general engineering design instrument and can provide a tool for educators to gather information about engineering design self-efficacy. Engineering design process steps used in the study can represent engineering design. Engineering design SE is highly dependent on engineering experiences. Motivation, outcomes expectancy, and anxiety were shown to relate to self-efficacy toward engineering design.
Jones, Paretti, Hein, & Knott (2010)	363 first-year engineering students at large state university (27.4% of all students) 78.5% male; 87.4% Caucasian	Engineering SE, expectancy for success, interest, attainment value, utility value, gender, time	SE for academic milestones (Lent et al., 1986) Self- and Task Perception Questionnaire (Eccles & Wigfield, 2005)	Expectancy- and value-related constructs predicted different outcomes. Both types of constructs are needed to understand students' achievement and career plans in engineering. Expectancy- and value-related beliefs decreased over 1st year for both genders Men reported higher levels of expectancy-related beliefs. Expectancy-related constructs predicted achievement better than value-related constructs, whereas value-related constructs better predicted career plans.

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Fantz, Siller, & DeMiranda (2011)	Pilot test: 78 junior-level engineering students Sample: 1st year engineering students	Engineering self-efficacy	MSLQ (Pintrich et al., 1991)	Significant differences in self-efficacy were only found between groups of students who had pre-engineering classes and engineering hobbies versus students who did not have these experiences. Based on the findings, engineering colleges with the goal of increasing self-efficacy of engineering students should consider focusing resources on developing K-12 technology and pre-engineering teachers.
Purzer (2011)	22 first-year engineering students in introductory design course	Verbal exchanges engineering SE student achievement	Team interaction Observation Protocol Coding Scheme Engineering SE survey	SE correlated with achievement. Students who initiated support-oriented conversations and did not engage in disruptive behaviors had high SE scores at the end of the semester. Verbal persuasions from peers were not directly related to SE or academic performance. Initial SE can predict certain verbal interactions an individual would engage in when working in a team.
Brown, & Burnham (2012)	First-year engineering students in ENGR 107	Math SE (problem math SE and courses math SE)	Mathematics Self-Efficacy Survey (MSES: Betz & Hackett, 1983)	Engineering students' self-efficacy beliefs are strongly tied to their successful navigation of the engineering curriculum. Mastery experiences were most powerful source of SE for students in engineering math course. Changes in students' math SE were inconsistent.

Table 1 (continued)

Author	Participants	Variables	Self-Efficacy Measures	Findings and Conclusion
Concannon & Barrow (2012)	746 engineering students 635 men 111 women	Engineering SE, engineering career outcome expectations, coping self-efficacy, year-level	LAESE	No significant differences in overall mean engineering SE scores were found by gender Overall, fifth year men had significantly lower mean ESE scores compared to all other groups. Men in their 1st year of engineering had significantly lower subscale scores compared to other groups of men. No significant difference in overall ESE scores nor SE subscale scores were found among 1st to 5th year women.
Schubert, Jacobitz, & Kim (2012)	60 students enrolled in ENGR 101 (Intro to Engineering) and ENGR 102 (Intro to Engineering Design)	Student knowledge, confidence, usage of design process	Survey of students' perceptions of knowledge of the engineering design process Designed Assessment of student confidence in applying engineering design concepts	Assessment data showed a significant overall increase in both student knowledge and confidence scores as well as significant individual incremental increases. Presentation-exercise combinations have been found useful as a meaningful first exposure of freshman students to the engineering design process.

students' beliefs in their capabilities to perform academic tasks. Students are asked to judge their general confidence to function successfully in engineering without an explicit reference to particular problems or tasks. One such measure is the Patterns of Adaptive Learning Scale (PALS; Midgley et al., 2000). The PALS includes a measure of academic self-efficacy, which refers to students' perceptions of their competence to do their class work. Another scale, the Generalized Self-Efficacy Scale (GSES; Schwarzer & Jerusalem, 1995) was designed to measure individuals' beliefs that they can perform novel or difficult tasks in various domains of functioning. This scale has been used by Dunlap (2005) to quantify software engineering students' self-efficacy in problem solving. In addition to PALS and GSES, a general measure of self-efficacy often administered to students in engineering programs is the Self-Efficacy for Learning and Performance Scale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991). The MSLQ manual states that there are two aspects of expectancy: expectancy for success and self-efficacy. Items for these aspects are combined in one scale. Sample items from the scales mentioned above are found in Table 2.

Table 2

General Self-Efficacy Measures Used and Sample Items

Author	Scale	How construct was defined	Sample Item(s)
Pintrich, Smith, Garcia, & McKeachie (1991)	Self-Efficacy for Learning and Performance Scale of the MSLQ	Self-efficacy is referred to as an aspect of expectancy	I'm confident I can understand the basic concepts taught in this course.
Schwarzer & Jerusalem (1995)	Generalized Self-Efficacy Scale	Self-efficacy - individuals' beliefs that they can perform new and difficult tasks in various domains of human functioning	When I am confronted with a problem, I can usually find several solutions. I can usually handle whatever comes my way.
Midgley et al. (2000)	Patterns of Adaptive Learning Scale (PALS)	Academic self-efficacy - students' perceptions of their competence to do their class work	I'm certain I can master the skills taught in class this year. I can do almost all the work in class if I don't give up. I can do even the hardest work in this class if I try.
Vogt, Hocevar, & Hagedorn (2007)	Motivated Strategies for Learning Questionnaire (MSLQ) and task-specific self-efficacy scale (O'Neil and Herl,1998)	Beliefs in capabilities to perform specific tasks	I can master the skills in my major. I will do well in one's major. I can understand the most basic concepts. I can understand the most complex concepts. I will receive better than average grades in my major.

As general measures, these scales are thought to be suitable for a broad range of applications. However, Bandura (2006) argued that there is no all-purpose measure of self-efficacy. He emphasized that a "one measure fits all" (p. 307) approach usually has limited explanatory and predictive value because the items are not in the context of the situational demands and circumstances that are unique to the domain of functioning. Researchers interested in examining the self-efficacy of engineering students should therefore utilize a differentiated set of efficacy beliefs associated with the various competencies in engineering.

Modified general self-efficacy measures. In an attempt to make general self-efficacy measures domain specific, researchers have modified items in existing general self-efficacy instruments (see Table 3). For example, the concept of engineering was integrated into the MSLQ instrument by replacing the generic label of "class" with "engineering classes" (Fantz, Siller, & DeMiranda, 2011). In their study of first and second-year engineering students' motivation, Jones, Paretti, Hein, and Knott (2010) adapted self-efficacy items from the Academic Milestones Scale (AMS) created by Lent, Brown, and Larkin (1986). The engineering self-efficacy scale items in the AMS were worded to include "engineering major" to help students situate their rating of confidence in their abilities (e.g., "How much confidence do you have in your ability to excel in your engineering major over the next semester?"). Lent et al. (1986) combined the Educational Requirements Scale and the Self-Efficacy for Technical/Scientific Fields to ask students to indicate their self-efficacy for completing the educational requirements and job duties performed in 15 science and engineering fields. The final scale was intended to measure self-efficacy in technical/scientific fields such as engineering. These efficacy belief scores were matched to corresponding career options.

Table 3

Modified General Self-Efficacy Measures Used and Sample Items

Author	Scale	How construct was defined	Sample Items
Marra, & Bogue (2006)	LAESE - Engineering Self-Efficacy 1	Belief in one's capabilities to organize and execute courses of action required to produce given attainments (Bandura, 1997, p. 3)	I can succeed in an engineering curriculum. I can succeed in an engineer curriculum while not having to give up participation in my outside interests (e.g., extra-curricular activities). I will succeed (earn an A or B) in an advanced math course. I will succeed (earn an A or B) in an advanced engineering course.
	LAESE - Engineering Self-Efficacy 2		I can complete the math requirements for most engineering majors. I can excel in an engineering major during the academic year. I can complete any engineering degree at this institution. I can complete the chemistry requirements for most engineering majors.
Fantz, Siller, & DeMiranda (2011)	Modified MSLQ to measure engineering self-efficacy with the replacement of "class" with "engineering classes"	People's judgment of their capabilities to organize and execute courses of action required in engineering coursework	I'm confident I can understand the basic concepts in my engineering classes. I expect to do well in my engineering classes. I'm confident I can do an excellent job on the assignments in my engineering classes. Considering the difficulty of my engineering courses and teachers, and my skills, I think I will do well in my engineering classes. I believe I will receive excellent grades in my engineering classes.
Jones, Paretti, Hein, & Knott (2010)	Self-Efficacy for Academic Milestones (Lent, Brown, & Larkin, 1986)	One's judgment of his or her ability to perform a task in engineering	How much confidence do you have in your ability to: Complete all of the "basic science" (i.e., math, physics, chemistry) requirements for your engineering major with grades of B or better?

The Longitudinal Assessment of Engineering Self-Efficacy (LAESE), developed by Marra and Bogue (2006), is designed to identify longitudinal changes in the efficacy beliefs of undergraduate students studying engineering. The items in the LAESE measure various "aspects of self-efficacy, confidence, and outcome expectations, all factors that have been shown to influence success in studying engineering" (Assessing Women and Men in Engineering, n. d.). The instrument includes items focusing on engineering-related self-efficacy such as, "I can complete the physics requirements for most engineering majors, and I can complete the math requirements for most engineering majors." It also contains expectancy items (e.g., "I will succeed, e.g., earn an A or B, in my physics courses).

A concern with current general engineering self-efficacy measures is the combination of items that involve expectancy and self-efficacy. *Expectancy for success* refers to the expectation that success will likely occur. On the other hand, self-efficacy refers to the beliefs that individuals have in their capabilities to perform a task. The anticipation of a future success in a performance (e.g., I believe I will receive an excellent grade in this class) does not necessarily translate to the belief that an individual can do the task (e.g., I can get an excellent grade in this class). Bandura (2006) stressed that items concerned with perceived capability should be phrased in terms of *can do* rather than *will do,* because the former is a judgment of capability whereas the latter is a statement of intention. Researchers who have used the LAESE in subsequent studies revised the *will do* items to *can do* items when they used the scale (e.g., Concannon & Barrow, 2009).

Engineering skills self-efficacy measures. Some researchers have sought to assess skills-specific self-efficacy in engineering. Inherent in a skills-specific measure is what it means to be an efficacious engineer. One approach to assessing skills self-efficacy is to present a set of specific problems to students and then ask them to rate their confidence for successfully solving each type of problem (Bong & Hocevar, 2002). However, there are instances when a specific skill is better reflected by using verbal descriptions of task components. For example, students estimate their confidence in their engineering design skills by judging their confidence to successfully perform tasks such as identify a design need, develop design solutions, and evaluate a design (e.g., Carberry et al., 2010).

Understanding that self-efficacy is context- and skills-specific rather than a global judgment of ability, other researchers have developed measures for task-specific self-efficacy in engineering (see Table 4). Kinsey, Towle, O'Brien, and Bauer (2008) designed a measure specifically for engineering students' self-efficacy for spatial tasks. Spatial ability is the ability to correctly visualize three dimensional objects when they are represented in two dimensions (Towle et al., 2005) and is relevant to designing and fabricating components for devices. Using portions of the Purdue Spatial Visualization Test (PSVT), they developed a self-efficacy test to assess students' self-confidence in being able to rotate objects given a prior example of a rotated object. Their protocol was based on a similar technique used to assess students' self-efficacy in solving algebra problems (i.e., Schunk, 1982).

Researchers have asserted that because engineering design is a central theme in the engineering profession, there is a need to investigate engineering students' confidence in their engineering design skills (Carberry et al., 2010; Purzer, 2011; Schubert et al. 2012). Engineering design tasks are applied or practical components of engineering consisting of several processes used in devising a system or a component to meet an identified need. Carberry et al. (2010) echoed other researchers' claims that design tasks are an important part of engineering education because they prepare students for the demands for new processes and products in various industries. Two measures have been used to assess engineering design self-efficacy. The first, created by Carberry et al., includes items based on a model of the design process as proposed in the Massachusetts Department of Education Science and Technology/Engineering Curriculum Framework. The second, designed by Schubert et al., consists of items based on a ten-step engineering design process from a textbook used in an engineering design class.

Bandura (2006) noted that "perceived efficacy should be measured against a level of task demands that represent gradations of challenges or impediments to successful performance" (p. 311). The measures created by Carberry et al. (2010) and Schubert et al. (2012) have items that reflect the varying level of task difficulty involved in the engineering design process. The items begin with a simple task of recognizing a design need, followed by developing a design given certain constraints, evaluating the design based on a defined set of criteria, even including redesign. Having levels of task difficulty helps students reflect on how much they believe in their abilities to surmount challenges. According to Bandura (2006), if the engineering task is easily performable, then everyone would be highly efficacious in engineering.

Baker et al. (2008) developed an instrument measuring perceived efficacy for tinkering and technical skills. The tinkering self-efficacy and technical self-efficacy instruments contain items that focus on possession (or lack thereof) of skills ("I do not have data analysis skills"), hobbies ("I do not have tinkering type hobbies"), and experience ("I do not have engineering experience"). Although tinkering and technical skills are certainly within the domain of engineering, items crafted in this way do not measure students' beliefs in their capabilities and therefore cannot be considered efficacy judgments.

The nature of questions and statements included in self-efficacy instruments can be problematic (Bong, 2006). Instruments that are inconsistent with Bandura's (2006) guidelines might be assessing something other than self-efficacy. Table 4 presents engineering skills self-efficacy measures and their respective items. In certain cases, items in the self-efficacy measure are personality statements such as, "I am inquisitive" and "I am not a logical thinker" (Baker et al., 2008), and do not represent self-efficacy as conceptualized by Bandura.

Table 4

Engineering Skills Self-Efficacy Measures Used and Sample Items

Author	Scale	How construct was defined	Sample Items
Baker, Krause, & Purzer (2008)	Technical Self-Efficacy	Confidence and belief in one's competence to learn, regulate, master and apply technical academic subject matter related to success in engineering.	I can statistically model a process. I do not have data analysis skills. I think practically. I understand the relationship of theory and application. I can develop/improve a product/system for manufacture of the product or implementation of the system. I am not a logical thinker.
Baker, Krause, & Purzer (2008)	Tinkering Self-Efficacy	Confidence and belief in one's competence to engage in activities such as manipulating, assembling, disassembling, constructing, modifying, breaking and repairing components and devices.	I have more experience than knowledge. I have a long history of tinkering on personal development projects. I have the knowledge and technical skills to create mechanisms or devices. I do not have spatial sense. I do not consider solutions before taking things apart. I am inquisitive. I do not work well with my hands. I try to understand how things work in order to fix problems. I do not understand technical drawings such as wiring diagrams.
Carberry, Lee, & Ohland (2010)	Engineering Design Self-Efficacy	Belief in ability to perform engineering design tasks which consists of devising a system, a component, or a protocol to meet an identified need.	Respondents were asked to rate: 1) their degree of confidence, 2) how motivated would they be, 3) how successful would they be, and 4) their rate of anxiety to perform the following tasks conduct engineering design: identify a design need research a design need develop design solutions select the best possible design construct a prototype evaluate and test a design communicate a design redesign

Table 4 (continued)

Author	Scale	How construct was defined	Sample Items
Schubert, Jacobitz, & Kim, (2012)	Assessment of Student Confidence in Engineering Design	Confidence in applying the concepts of the design process	I can recognize the needs to be addressed by a problem and formulate those needs in clear and explicit items. I can select a solution that best satisfies the problem objectives. I can build and evaluate a prototype or final solution. I can recognize when changes to a solution may be necessary through iteration in the design process. I can document the design process.
Purzer (2011)	Engineering Self-Efficacy	Confidence in one's ability to perform tasks aligned with the objectives of an introductory design course	Please indicate how confident you are in your ability to… 1. explain steps of the engineering design process 2. use the steps of the engineering design process to solve an engineering design problem 3. build a prototype model using appropriate cutting, joining, and shaping tools 4. use a CADD (computer-aided drafting and design) software to document a design concept.

Qualitative measures of engineering self-efficacy. Some scholars have taken a qualitative approach in their investigation of engineering self-efficacy. Qualitative studies in engineering self-efficacy have explored aspects of engineering skills. For example, Baker and Krause (2007) asked students to list what they thought were characteristics of an individual with good tinkering skills and of an individual with good technical skills. They ranked the themes and found that technical or tinkering skills represented different aspects of engineering. In another study, Baker et al. (2007) relied on nine graduate students' reflection papers, classroom observations, and focus group transcripts to document the kind of educational experiences that are most likely to bring about changes in students' tinkering self-efficacy and technical self-efficacy. In other studies, open-ended survey questions and semi-structured open-ended interview protocols have been used to investigate the influence of first-year engineering experiences on students' self-efficacy. When asked to describe an experience that affected their confidence in succeeding in an introductory class in engineering, first-year engineering students mentioned experiences that aligned closely with the hypothesized sources of self-efficacy (Hutchison et al., 2006; Hutchison-Green, Follman, & Bodner, 2008). The results of these studies support Bandura's (1997) framework for the sources of self-efficacy.

Mixed method approaches have also been used to conduct research on engineering self-efficacy. Such approaches involved the analysis of scores collected on a self-efficacy instrument (e.g., Academic Efficacy Scale) in combination with analysis of qualitative data such as guided journal entries (i.e., Dunlap, 2005), responses to open-ended items on a survey (i.e., Hutchison et al., 2006), or class observations (i.e., Schubert et al., 2012). In effect, quantitative and qualitative data were "mixed" in some way to form a more complete picture of self-efficacy in engineering.

Engineering Self-Efficacy and Gender

Traditionally, engineering has been a male-dominated field. Clement (1987) provided evidence that women had lower self-efficacy than did men with regard to traditionally male occupations. She also reported that self-efficacy failed to predict women's consideration of traditionally male occupations. In the past years, several efforts have been made to increase the number of women in engineering. However, the decline in the number of engineering degrees awarded to students in the United States has raised concerns about student retention regardless of gender. Researchers have examined gender differences within college-level academic settings. They have looked into the relationship between women's and men's self-efficacy and their choice, performance, and persistence in engineering programs. Hackett, Betz, Casas, and Rocha-Singh (1992) found that gender was not a significant predictor of self-efficacy. Rather, academic self-efficacy mediated the effects of gender on college level academic achievement. Few to no gender differences in SAT scores, college GPA, or self-efficacy have been observed among engineering students (Hackett et al., 1992; Schaefers, Epperson, & Nauta, 1997; Vogt, 2003). Some researchers have found that women perceive more social support and fewer social barriers to their pursuit of engineering degrees than do men (Jackson, Gardner, & Sullivan, 1993; Lent et al., 2005; Zeldin & Pajares, 2000).

Despite these trends, inconsistent findings from other studies make it difficult to form generalizations regarding self-efficacy and gender. Hutchison et al. (2006) and Concannon and Barrow (2008) did not find evidence of gender variations in the self-efficacy of first-year engineering students. Other researchers have likewise reported that women did not differ significantly from men across most social cognitive variables in science and engineering fields (Lent et al., 1984, 1986; Lent, Brown, Sheu, et al., 2005). In some studies, women's self-ratings of their abilities were lower than men's self-ratings when students compared themselves to their peers in engineering (Betz & Fitzgerald, 1987; Jackson et al., 1993; Jagacinski, LeBold, & Linden, 1987; Jones et al., 2010). Vogt et al. (2007) found significant gender differences in students' self-efficacy as well. Once again, men reported higher self-efficacy scores than did women.

Most research on self-efficacy in engineering has been focused on students' overall performance in their engineering programs. Baker et al. (2007) asserted that students may be generally self-confident but lack self-efficacy related to specific areas of skill, knowledge, or ability. Tinkering self-efficacy has been considered to be a factor related to the low percentage of women in engineering. Women's lack of experience in using tools and machinery might explain their lower scores than men in tinkering self-efficacy (Baker et al., 2007). Although men and women are equally prepared academically to pursue undergraduate degrees in engineering and willing to learn engineering skills, women's lack of confidence in their tool and machine skills may have discouraged them from pursuing engineering degrees (Schreuders, Mannon, & Rutherford, 2009).

A strong sense of efficacy in engineering, especially for women, might help students persist in engineering programs and enable them to become practicing engineers (Marra et al., 2009). Gender differences in self-efficacy could also help explain why women and men report different motives for pursuing an engineering degree. Further examination of the relationship between engineering self-efficacy and gender is needed. Moreover, gender differences in engineering skills self-efficacy have yet to be investigated, particularly at the undergraduate level.

Engineering Self-Efficacy and Year Level

Scholars have investigated the relationship between engineering self-efficacy and year level (i.e., freshman, sophomore, junior, senior). Students' year levels help describe the length of time they have been in their engineering programs. Marra and Bogue (2006) proposed that students further along in their engineering degree programs would have higher engineering self-efficacy than those who are just beginning. Students' successful completion of requirements in their engineering programs likely enhances their engineering self-efficacy (Bandura, 1997). However, few researchers have examined engineering self-efficacy across undergraduate year levels.

Most of the research on engineering self-efficacy has focused on the first-year college experience (e.g., Concannon & Barrow, 2008; Hutchison et al., 2006; Hutchison-Green et al., 2008). Results of such studies have provided a useful look at the first-year engineering experiences that influence students' self-efficacy. First-year engineering students placed significant weight on social comparisons compared to second-year students (Hutchison-Green et al., 2008). Researchers have also compared how first-year students build and modify their efficacy beliefs as they advance in the engineering curriculum. Interviews conducted by Hutchison, Follman, and Bodner (2007) revealed that mastery experiences influenced second-year students' confidence in succeeding in an engineering course. Results suggested that students' self-efficacy is directly affected by their learning environment (Hutchison et al., 2007).

Considering that the learning environment changes as students advance in their engineering programs, researchers have tried to determine whether students' engineering self-efficacy differs as a function of the number of years they have been in their programs (e.g., Brainard & Carlin, 1998; Marra et al., 2009). Concannon and Barrow (2009) reported that fourth-year students had higher engineering self-efficacy scores than fifth-year students. However, they attributed this result to the fact that a certain percentage of the fifth-year students were students who transferred into the College of Engineering. Thus, the fifth-year status given to these students did not reflect the actual number of years these students have been in their engineering program. When they excluded the fifth-year students' data from their analysis, Concannon and Barrow (2009) found no significant differences in engineering self-efficacy from first-year to fourth-year students. In a later study, the researchers found that all first-year students had significantly lower self-efficacy scores compared to upperclassmen (Concannon & Barrow, 2012). Moreover, regression analysis showed that engineering self-efficacy significantly predicted students' intentions to persist in engineering at all year-levels. Self-efficacy explained 17.2%, 40.2%, 19.8%, 33.9%, and 23.5% of the variance in first-year, second-year, third-year, fourth-year, and fifth-year students' intentions to persist, respectively.

Researchers have also explored the relationship between self-efficacy and year level by gender. Women's self-efficacy scores were not significantly different when analyzed by year-level (Concannon & Barrow, 2012; Marra & Bogue, 2006; Marra et al., 2009). In contrast, men's self-efficacy scores were significantly different as a function of years in the program (Concannon & Barrow, 2012). Men in their first year of engineering had lower self-efficacy scores compared to their upperclassmen counterparts. Further investigation revealed that upperclassmen had significantly higher self-efficacy compared to freshmen men and women.

Results from studies on the relationship between engineering self-efficacy and year-level have been inconsistent. Inclusion of a third variable, such as gender or intent to persist, has helped tease out significant differences in engineering self-efficacy among undergraduate engineering students. Given the limited number of studies on engineering self-efficacy of students at different levels in their engineering programs, researchers do not have conclusive evidence about the effect of the number of years students have been in their program on their engineering self-efficacy. The few researchers who have investigated self-efficacy across year levels only focused on students' general engineering self-efficacy. Studies that examine engineering skills self-efficacy across year levels have yet to be conducted.

Engineering Self-Efficacy and Engineering Major

The engineering profession is directed towards the application and advancement of skills based upon a body of distinctive knowledge in mathematics, science, and technology acquired through education and professional formation in an engineering discipline (Nguyen, 1998). Typically, students decide to major in engineering because they were told they were good in mathematics and/or science. Students' familiarity with and perceptions of engineering specialties also influence their choice of engineering majors and their career decision-making self-efficacy (Shivy & Sullivan, 2005). Pre-collegiate informal experiences may have also exposed students with real engineers in the field. Even students' toys or hobbies help students develop an understanding of engineering principles. According to Fantz et al. (2011), there are some relationships between engineering disciplines and toys. Examples of these relationships are civil engineering and LEGO® building blocks, mechanical engineering and Erector® Sets, and computer engineering and video game production. They hypothesized that engineering exposure affects the self-efficacy of engineering students, particularly freshmen. Moreover, engineering self-efficacy was related to students' exposure to engineering and to the discipline they choose to pursue.

Although engineers may have a general role of implementing, applying, operating, designing, developing, and managing products and processes, the type of work they do varies based on their chosen field of study or major (e.g., chemical, civil, electrical, mechanical; Nguyen, 1998). Each engineering discipline requires a specialized skill set that corresponds to the demands of a student's future profession. Thus, the engineering curriculum for each major is designed for students to learn concepts specific to their engineering discipline and to connect what they learn with their future roles as engineers in their chosen discipline (Dunsmore, Turns, & Yellin, 2011).

Some evidence has shown that students' efficacy beliefs are related to their engineering discipline. For example, Towle et al. (2005) examined the correlations between the self-efficacy and spatial ability of students who are declared engineering majors and students who have not declared a major. They found that the relationship between students' self-efficacy and their spatial ability was significant only for those students who had declared engineering as a major. Towle et al. also found a difference in the spatial abilities of students in a mechanical engineering design course and a civil engineering course and hypothesized that students' beliefs in their spatial ability could be improved by taking computer-aided design classes tailored to engineering majors. Kinsey et al. (2008) compared the spatial ability scores and self-efficacy of students from various engineering majors (i.e., mechanical, electrical, civil, and civil technology). They reported that mechanical engineering majors had significantly higher self-efficacy scores than civil engineering majors and civil technology majors.

Concannon and Barrow (2008) also examined differences in mean scores of engineering self-efficacy across engineering disciplines. They found no statistically significant differences in self-efficacy scores among students majoring in biological, chemical, civil, computer/electrical, or industrial engineering. It bears noting, however, that all participants in the study were freshman engineering students. At this point in their program, they had not taken engineering major courses tailored to their areas of specialization.

Findings with regard to major and self-efficacy are mixed. Researchers examined either general engineering self-efficacy or a particular type of engineering skills self-efficacy (e.g., spatial ability self-efficacy) in relation to engineering major. Further research is necessary to investigate whether students' engineering majors influence their general engineering self-efficacy, a type of engineering self-efficacy, or both. To date, research simultaneously investigating the influence of engineering major on the different types of engineering self-efficacy is limited.

Engineering Self-Efficacy and Academic Achievement

The predictive effect of self-efficacy on students' academic achievement (e.g., grades) has been researched extensively in the academic setting, yet few studies have been conducted in the domain of engineering. Bandura (1997) proffered that students' beliefs about their capabilities influence their academic achievement. Psychological variables, such as self-efficacy, have been shown to predict engineering students' grades (Hsieh, Sullivan, Sass, & Guerra, 2012; Lent et al., 1984, 1986). For example, Hackett et al. (1992) showed that academic self-efficacy was the strongest predictor of cumulative college GPA. Using stepwise regression analysis, the researchers found that SAT mathematics scores, faculty encouragement, and high school GPA, along with academic self-efficacy, were positive predictors of engineering students' college GPA. Similarly, Jones et al. (2010) conducted a stepwise regression analysis of predictors (i.e., expectancy and self-efficacy) of engineering students' first year GPA. Self-efficacy alone accounted for 35 percent of the variance in GPA, and expectancies for success accounted for an additional 3 percent of the variance. Lent et al. (1986) found that self-efficacy accounted for additional significant variance in students' technical GPA after controlling for high school rank and SAT mathematics score. Researchers have not fully explored how students' efficacy beliefs in doing engineering tasks affect their performance in engineering programs.

Lent et al. (1984, 1986) reported that students in scientific and technical programs who had high self-efficacy generally achieved higher grades than those students with low self-efficacy. With the intention to focus only on students in engineering programs, Hackett et al. (1992) found that both occupational and academic milestones self-efficacy were significantly correlated with college GPA. Academic self-efficacy mediated the effect of prior academic achievement on college-level academic achievement. Other researchers have explored task-based self-efficacy in engineering and its relationship to academic success. For example, Vogt et al. (2007) and Vogt (2008) showed that self-efficacy had the strongest significant relationship with GPA compared to other study variables (e.g., academic integration, discrimination, academic confidence, help-seeking, effort, and critical thinking).

Correlations between self-efficacy and academic achievement have also been investigated in the context of specific engineering courses. Using a sequential mixed-methods design approach, Purzer (2011) examined the relationships among discourse actions, self-efficacy, and achievement of students in an introductory course in engineering. Engineering students' self-efficacy scores were collected at the beginning and at the end of a semester. Embedded performance assessments (e.g., design projects) were used to measure learning related to the course objectives. Although beginning and end of semester self-efficacy scores were not significantly correlated with student achievement, the self-efficacy gains during the semester were found to have a significant correlation with achievement scores.

The studies presented above describe the positive relationship between self-efficacy and academic achievement. Students with high self-efficacy tend to perform better academically than students with low self-efficacy. Self-efficacy has been found to predict overall achievement in engineering. However, concerns about the correspondence between the engineering self-efficacy and achievement outcomes still prevail. The self-efficacy measures used in these studies have varied from general to task-specific but have often lacked correspondence to the achievement outcomes used. Results reported must therefore be interpreted cautiously with this limitation in mind. Self-efficacy measures that correspond to the outcome of interest achieve better explanatory and predictive power (Bandura, 2006; Pajares, 1996).

Engineering Self-Efficacy and Persistence

The relationship between self-efficacy and persistence in engineering has been investigated in numerous ways. As noted earlier, the use of self-efficacy measures in engineering-related domains (i.e., mathematics and science) as a proxy for gauging engineering self-efficacy is not uncommon. For example, Schaefers et al. (1997) found that mathematics and science self-efficacy significantly predicted persistence in engineering. In other studies, confidence in mathematics and science skills were correlated with persistence in engineering programs (Eris et al., 2010).

Researchers have examined the relationship between self-efficacy in engineering and students' persistence in engineering degree programs. Some have found that students with high self-efficacy in technical/scientific fields not only obtained high grades but also persisted longer in these fields (Lent et al., 1984). Lent and colleagues (2010) suggested that efforts to promote engineering students' self-efficacy may offer a viable means to solidify students' intentions to persist in engineering. The relationship between self-efficacy and the intent to persist may also differ for male and female students. For example, Concannon and Barrow (2010) found that men's intentions to persist in their engineering degree programs were predicted by their beliefs in their ability to complete coursework requirements, whereas women's intentions to persist were predicted by getting an "A" or a "B" on a test or in a difficult course.

Persistence has been defined in various ways, however. Some scholars have measured persistence in terms of the number of quarters students have actually completed (Lent et al., 1984). Others have opted to define persistence in terms of students' current enrollment status in their academic program (Schaefers et al., 1997). Eris et al. (2010) defined persistence in relation to the engineering domain in two dimensions: academic persistence and professional persistence. Academic persistence meant graduating with an undergraduate engineering degree, whereas professional persistence referred to the intention to practice engineering for at least three years after graduation. They noted that students who graduate with engineering degrees do not necessarily practice engineering.

Self-Efficacy and Other Motivation Constructs

Numerous factors contribute to students' success in engineering. Educators and researchers desire to better understand the factors that affect students' decisions to remain in engineering programs and their ability to perform well enough to be retained (Bernold, Spurlin, & Anson, 2007). Examining multiple motivation variables may be helpful for understanding the educational goals that engineering students pursue (Harackiewicz, Barron, & Elliot, 2000; Heyman, Martyna, & Bhatia, 2002). Motivation variables, such as achievement goal orientation and task value, have been found to predict academic performance and persistence in academic programs. I next discuss these variables as they have been examined within the concept of engineering.

Achievement goal orientations. Some researchers have taken interest in engineering students' achievement goal orientation and how this relates to achievement behavior. Achievement goals refer to the purpose or reason engineering students pursue academic learning tasks (Pintrich & Schunk, 1996). These goals involve the pursuit of competence in achievement situations and represent students' motivational orientation in certain situations, such as engineering courses (Harackiewicz, Barron, & Elliot, 1998). Students can pursue competence for two very different reasons: they may strive to demonstrate their competence to others (performance goal), or they may strive to develop competence for mastering or learning how to do the task (mastery goal) (Middleton & Midgley, 1997; Pintrich, 2000). Evidence demonstrated consistent and positive links of mastery goals to many educational outcomes; on the other hand, the effect of performance goals on similar outcomes is inconsistent (Harackiewicz et al., 1998).

Elliot (1999) noted that achievement goal researchers have relied primarily on the performance-mastery dichotomy in differentiating competence-based endeavors. He proposed that a better way of looking at achievement goals was through approach and avoidance motivation. Unlike students who want to learn or who want to attain success, some students may be motivated to avoid failure and have low competence expectancies. Performance-avoidance goals emphasized on avoiding unfavorable judgments of competence (Elliot & Church, 1997). Within a trichotomous achievement goal framework, three independent goals are delineated: a *mastery goal*, focused on developing competence or task mastery; a *performance-approach goal*, focused on attaining perceptions of competence relative to others; and a *performance-avoidance goal*, focused on avoiding perceptions of incompetence relative to others (Elliot, 1999). Mastery goals have been associated with positive achievement outcomes such as good grades, high test scores, and deeper learning. Performance-approach goals facilitate both adaptive and maladaptive achievement behavior. Performance-avoidance goals elicit negative affective, cognitive, and behavioral processed that lead to negative outcomes (Elliot & Church, 1997).

Students' college-related achievement goals have been shown to predict overall GPA (Durik, Lovejoy, & Johnson, 2009; Hsieh, Sullivan, & Guerra, 2007). Mastery goals predict enrollment in major courses, whereas performance goals predict long-term academic performance (Harackiewicz et al., 2000). Students who adopted mastery goals more than performance-avoidance goals were likely to have high GPAs (Hsieh et al., 2007).

The achievement goals students pursue have also been found to be related to students' self-efficacy. Engineering students with high self-efficacy are more likely to adopt mastery goals compared to those who have low self-efficacy (Hsieh et al., 2012). Although research on the relationship between achievement goals and academic self-efficacy has contributed to understanding students' motivation and general academic achievement, evidence of this relationship in the field of engineering is scarce (Hsieh et al., 2012).

Task values. Researchers have also examined students' expectancies and values to explain what influences their effort, performance, and persistence. In expectancy-value theory, expectations for success (i.e., beliefs about how well one will do in an activity) and subjective task value (i.e., value placed on an activity) are assumed to influence directly achievement choices (Eccles, 2005; Wigfield & Eccles, 2000). Task value has four components: attainment value, intrinsic value, utility value, and cost (Eccles, 2005). Attainment value is described as the personal importance of doing well on a specific task (Eccles & Wigfield, 2002). Intrinsic value is the enjoyment the individual derives from performing the activity or the internal drive or interest an individual has for the task itself. Utility value refers to the usefulness of the task and how the task fits into an individual's future plans (Wigfield & Eccles, 2002). Perceived cost is conceptualized in terms of the demands of engaging in the task, such as amount of time and effort needed to succeed, the sacrifices involved to accomplish the task, and the degree of failure the task provokes (Eccles, 2005).

Researchers have shown that task values predict course plans and enrollment decisions in mathematics and physics (Bong, 2001a; Meece, Wigfield, & Eccles, 1990), test-taking effort, and test performance (Cole, Bergin, & Whittaker, 2008). In some studies, usefulness and importance have been shown to affect persistence and achievement (Pintrich & Zusho, 2002; Wigfield & Eccles, 2000). These findings suggest that if students do not perceive the usefulness or importance of an engineering course, they might not put much effort into class activities and their academic performance may suffer.

Students develop subjective task values for different tasks and activities depending on the nature of the task and how well the task aligns with their goals and needs (Eccles, 2005). In the field of engineering, few studies have investigated academic performance and persistence in engineering from the task value perspective. Students' perceived value of tasks and activities influence their choices to engage in engineering activities and persist in earning engineering degrees (Matusovich, Streveler, & Miller, 2010). In some studies, researchers have examined engineering students' value of tasks, projects, and course activities by measuring only two or three of the value components. Panchal, Adesope, and Malak (2012) investigated engineering students' perceptions of the value of design projects and found that self-rated project performance was significantly related to attainment value and intrinsic value but not to utility value. Burn and Holloway (2006) examined engineering majors' perceptions of the attainment value (importance) and utility value (usefulness) of learning programming in an introductory course on computers and programming. Their study showed that students' interest in weekly programming assignments was related to self-reported proficiency in programming. Without individual student grades, they could only speculate that students' perceptions about the importance and usefulness of programming were directly associated with levels of achievement based on historical data.

Students' perceptions of engineering seem to tell part of the story about why they stay in the field or leave. In general, students agree that engineering is beneficial to society yet they tend to feel that much effort is needed to earn an engineering degree and maintain a career (Li, McCoach, Swaminathan, & Tang, 2008). Contrary to engineering faculty members' belief that college students seek classes that are easy, engineering students are typically not averse to a heavy workload if they see the benefit of putting in the effort (Martin, Hands, Lancaster, Trytten, & Murphy, 2008). These students are up to the challenge as long as they perceive they can do what the courses require.

According to Matusovich et al. (2010), different patterns exist in the types of value students assign to earning an engineering degree. Situations in which attainment, interest, and utility values are low and cost values are high can lead students to leave their engineering programs. On the other hand, low attainment values, high utility value, and moderate interest can lead to persistence. Their study confirmed "that one value category alone is not enough to explain persistence" (Matusovich et al., 2010, p. 299). In certain cases, students who leave engineering in good standing were likely to have lost interest in engineering (Besterfield-Sacre et al., 1997). In this way, task value and self-efficacy appear to influence academic outcomes.

Other researchers have ventured towards determining which expectancy-value constructs best predict achievement and persistence in engineering. Jones at al. (2010) reported that both self-efficacy and expectancy for success were significant predictors of engineering GPA. They found that women's interest predicted their engineering GPA. Data collected at the start and at the end of students' first year in engineering were examined to determine whether the types of value students' assigned to engineering and engineering activities changed in relation to the pursuit of their engineering degrees. Using the data from the start of the first year, they found that extrinsic utility value and intrinsic interest value predicted students' pursuit of their engineering degrees. By the end of students' first year, only utility value predicted likelihood of pursuing an engineering degree. They concluded that expectancy- and value-related constructs predicted different outcomes; the expectancy for success predicted achievement better than task value, whereas task value predicted career plans better than expectancy.

Review Summary and Problem Statement

The review of the literature on engineering self-efficacy points to three major areas for improvement to address gaps in what is known about the measurement of engineering self-efficacy. First, self-efficacy measures have been used to assess engineering self-efficacy at varying levels of specificity. Despite the various ways that researchers have attempted to measure engineering self-efficacy, few have been true to Bandura's (1997) definition of self-efficacy and have been closely aligned with his (2006) guidelines for creating self-efficacy scales. Lent et al. (1984) even noted that although the results of their study support the theory of self-efficacy, their study had conceptual and methodological shortcomings. Their measures of self-efficacy did not adequately operationalize the concept of self-efficacy rather these reflected general self-confidence. As Bong (2006) emphasized, self-efficacy measures should include questions and statements that not only ask about students' generalized perceptions of competence in engineering but also about their confidence in their capabilities to successfully perform a task under specified circumstances.

Second, existing measures do not seem to adequately cover the engineering domain and therefore may not accurately predict academic achievement. Academic performance in three levels are vital for success in engineering: general performance, performance of specific engineering tasks, and performance in specific engineering courses (Levin & Wyckoff, 1990). Items in engineering self-efficacy measures must include the skills required to carry out engineering tasks. Moreover, the items in the measure should have a level of specificity corresponding to the researcher's goal (Bandura, 2006). Judgments of capabilities matched to specific outcomes afford the greatest prediction of academic and/or behavioral outcomes (Bandura, 1986). To date, no study has examined the predictive utility of a general engineering self-efficacy scale and that of an engineering skills self-efficacy scale on academic performance and intent to persist in engineering.

Third, motivation researchers have learned how students' beliefs, values, and goals relate to their achievement behaviors by drawing on three theoretical perspectives of motivation: social cognitive theory, achievement goal theory, and expectancy-value theory. Research findings point to the need to integrate motivation constructs to better understand academic performance and persistence in engineering. Researchers need to continue to examine how motivation constructs operate within the domain of engineering. Successful performance and retention in engineering programs depend not only on students' knowledge and skills students learn, but also on their attitudes and beliefs (Besterfield-Sacre et al., 1997).

Copyright © Natasha Johanna A. Mamaril 2014

Chapter 3: Methodology

The purpose of the study was to develop and evaluate engineering self-efficacy scales to capture the different ability beliefs undergraduate engineering students hold and to examine if two types of engineering self-efficacy (general engineering self-efficacy and engineering skills self-efficacy) are significant predictors of achievement and intent to persist in engineering.

A quantitative survey design approach was used for this study. The survey was administered via the online survey program Qualtrics. This study included the development and evaluation of engineering self-efficacy scales for college students and the examination of the predictive validity of engineering self-efficacy measures. The development and validation of the Engineering Self-Efficacy Scales involved: (a) item development and assessment of content validity, (b) evaluation of scale reliability and construct validity, and (c) establishment of concurrent and predictive validity. Construct validity was further explored by correlations with other motivation constructs (achievement goal orientations and task value).

Research Questions and Hypotheses

This study was guided by the following research questions:

1. What are the psychometric properties of the measures designed to assess general engineering self-efficacy and engineering skills self-efficacy?

   Hypothesis 1a: Corresponding items for both measures will have high inter-item correlations.

   Hypothesis 1b: The engineering self-efficacy measures will have positive correlations with each other.

Hypothesis 1c: The factor structure of the general engineering self-efficacy measure will be unidimensional.

Hypothesis 1d: The factor structure of the engineering skills self-efficacy measure will be multidimensional with three differentiated factors (i.e., tinkering skills, technical skills, and engineering design).

2. Are there mean differences in the engineering self-efficacy scores of college students as a function of gender, year level, or major?

   Hypothesis 2a: Men will report higher self-efficacy scores than women will.

   Hypothesis 2b: Upperclassmen ad lowerclassmen will report similar levels of general engineering self-efficacy. Upperclassmen will report higher engineering skills self-efficacy scores than lowerclassmen will.

   Hypothesis 2c: Mechanical and civil engineering majors will report higher tinkering skills self-efficacy and engineering design self-efficacy than students in other engineering majors.

3. What is the unique contribution of each of the following: engineering self-efficacy, achievement goals, and task value to the prediction of achievement and intent to persist?

   Hypothesis 3a: Engineering self-efficacy will contribute to the prediction of achievement and intent to persist in engineering.

   Hypothesis 3b: Achievement goals will contribute to the prediction of achievement but not of intent to persist in engineering.

   Hypothesis 3c: Task value will contribute to the prediction of achievement and intent to persist in engineering.

Participants

Fall 2012 - Pilot Study. A total of 136 engineering students from two southeastern universities ($n_1 = 72$, $n_2 = 64$) completed the pilot survey. Of the students, 84% were Caucasian, 6% African American, 4% Hispanic/Latino, and 63% were male. The sample comprised of freshmen (29%), sophomores (36%), juniors (19%), seniors (13%), and students pursuing their second bachelor's degree (3%). The students were from different engineering major programs: 23% computer engineering, 22% mechanical engineering, 15% bioengineering, 11% civil engineering, 11% mining engineering, and 9% materials science engineering.

Spring 2013. A total of 321 engineering students from two southeastern universities ($n_1 = 224$, $n_2 = 97$) completed the survey at the beginning of the spring semester. The majority of the students were Caucasian (89%) and male (75%). The distribution by year level was as follows: 39% juniors, 31% sophomores, 23% seniors, and 6% freshmen. The students majored in mechanical engineering (33%), civil engineering (18%), industrial engineering (9%), chemical engineering (8%), and biosystems engineering (8%). There were a few students who majored in mining engineering (6%), electrical engineering (6%), and materials science engineering (5%).

Procedure

A meeting was held to inform the Dean of Academic Affairs of my intention to visit engineering classes to talk about the current study and to invite students to participate in the study. A curriculum matrix of the eight undergraduate programs in the College of Engineering was created to help identify classes from which to recruit (see Appendix B). Classes that were offered in fall 2012 and spring 2013 that had students from different year levels were chosen. Emails were sent to the department chairs to request five minutes of class time for the presentation of the study and to recruit participants. Department chairs gave their approval to visit classes in their departments. I visited eight engineering classes in fall 2012 and 23 classes in spring 2013 to recruit participants for the study. In addition, a research assistant at the other university visited three engineering classes to recruit participants for the spring 2013 survey.

Invitations with the survey link were emailed to engineering students (see Appendix C). At least four email reminders were sent until the close of the data collection period. Data for the final engineering self-efficacy measure were collected in spring 2013 semester.

Item Development and Assessment of Content Validity

I developed a pool of engineering self-efficacy items specific to engineering activities considered essential to undergraduate engineering students. The developed items were reviewed by a panel of experts who were asked to assess content validity of the Engineering Self-Efficacy Scale (DeVellis, 1991). The panel included five experts in the fields of engineering, engineering education, and educational psychology. Experts in the field of engineering were consulted to verify whether the items adequately covered the domain of engineering. Prior to the pilot test, three experts reviewed the initial scale. Following the panel's initial review of the items, a group of engineering graduate and undergraduate students (n = 14) took the survey and provided comments on item wording and clarity. After the pilot test, two more experts (one in engineering, one in engineering education) reviewed the scale. In total, five experts provided feedback on item relevance, clarity, and conciseness. Based on the experts' feedback and students' comments, I removed and/or revised items as necessary. The remaining items were then included in the pilot version of the scale that was used in the pilot test. Items are worded to begin with "I can" so as to emphasize the perception of one's capability to perform a task (Bandura, 2006). Two types of self-efficacy measures resulted: general engineering self-efficacy scale and engineering skills self-efficacy scale, which are described in the next section.

Instrumentation

Each of the motivation variables used in this study with the exception of the engineering self-efficacy scale was assessed with previously validated scales often used in studies of academic motivation. Using a 6-point Likert-type scale, students rated their level of agreement to statements related to the motivation variables. In the self-efficacy scales, students assessed their level of certainty that they can perform general and task-specific activities in engineering using a 6-point Likert-type scale (1 = *completely uncertain*; 6 = *completely certain*). I next describe the self-efficacy measures in detail.

General Engineering Self-Efficacy Scale. An initial pool of six items designed to assess general engineering self-efficacy was created by adapting items from previously published, validated scales (see Table 5). The items included in this scale focus on students' perceptions of their capability to perform generic tasks in most engineering courses, particularly referring to learning engineering content and competence in doing engineering coursework in general. Items were adapted from Bong (2001a) and were similar to the academic efficacy items in the Patterns of Adaptive Learning Scales (PALS) by Midgley et al. (2000). The items in the current scale were adapted for the domain of engineering.

Table 5

Items for General Engineering Self-Efficacy Scale for College Students

Item Code	Scale Items
GESE25	1. I can master the content in the engineering-related courses I am taking this semester.
GESE26	2. I can master the content in even the most challenging engineering course if I try.
GESE27	3. I can do a good job on almost all my engineering coursework if I do not give up.
GESE28	4. I can do an excellent job on engineering-related problems and tasks assigned this semester.
GESE29	5. I can learn the content taught in engineering-related courses.
GESE30	6. I can earn a good grade in my engineering-related courses.

Note. GESE = General Engineering Self-Efficacy, SE = Self-Efficacy. Items were adapted from Bong (2001a).

Engineering Skills Self-Efficacy Scale. An initial pool of 21 items was created by adapting items from previously published, validated scales and by developing new items based on field standards and qualitative studies in engineering self-efficacy (see Table 6). These items assessed engineering students' beliefs in their abilities to perform engineering tasks related to engineering coursework. Nine items were derived from "General Criterion 3. Student Outcomes" set by the Accreditation Board for Engineering and Technology (ABET; www.abet.org). These nine items reflect engineering skills expected from graduates of undergraduate engineering programs. Evaluation of student performance must be based on the demonstration of specific skills required for the completion of an engineering degree. Moreover, these skills are linked to three fundamental engineering activities that Schreuders et al. (2009) considered to be specific to engineering disciplines: designing, building, and analysis.

Table 6

Items for Engineering Skills Self-Efficacy Scale for College Students

Item Code	Scale Items	Source
Engineering Skills Self-Efficacy Items		
ESSE1	1. I can perform experiments independently.	ESSE1 and ESSE2 – Items adapted from Schreuders et al. (2009) and aligned with ABET program learning outcomes
ESSE2	2. I can analyze data resulting from experiments.	
ESSE3	3. I can orally communicate results of experiments.	ESSE3 and ESSE4 - New items aligned with ABET program learning outcomes
ESSE4	4. I can communicate results of experiments in written form.	
ESSE5	5. I can work with tools and use them to build things.	ESSE5, ESSE6, ESSE7, ESSE8, and ESSE9 - Items adapted from Schreuders et al. (2009) and aligned with ABET program learning outcomes
ESSE6	6. I can work with tools and use them to fix things.	
ESSE7	7. I can design new things.	
ESSE8	8. I can solve problems using a computer.	
ESSE9	9. I can work with machines.	
Tinkering Self-Efficacy Items		
ESSE10	10. I can build machines.	ESSE10 and ESSE11 – Items adapted from Schreuders et al. (2009)
ESSE11	11. I can fix machines.	
ESSE21	12. I can manipulate components and devices.	ESSE21, ESSE22, and ESSE26 - New items developed based on Baker et al. (2007)
ESSE22	13. I can assemble things.	
ESSE26	14. I can disassemble things.	
Technical Self-Efficacy Items		
ESSE23	15. I can learn academic subject matter in engineering.	New item developed based on Baker et al. (2007)
ESSE24	16. I can apply technical concepts in engineering.	ESSE24 and ESSE25 - New items developed based on Baker et al. (2007) and aligned with ABET program learning outcomes
ESSE25	17. I can master engineering subject matter	
Engineering Design Self-Efficacy Items		
ESSE13	18. I can identify a design need.	ESSE13, ESSE15, ESSE18, and ESSE20 – Items taken from Carberry et al. (2010) and Schubert et al. (2012)
ESSE15	19. I can develop design solutions.	
ESSE18	20. I can evaluate a design.	
ESSE20	21. I can recognize changes needed for a design solution to work.	

Note. ESSE = Engineering Skills Self-Efficacy.

The remaining 12 items are associated with specific tasks covered in engineering coursework. These items were crafted to differentiate levels of task difficulty as well. Five items were related to tinkering skills, and three items involved technical skills. Baker and Krause (2007) noted that the ABET Criterion 3 outcomes do not incorporate skills associated with tinkering and technical activities. They argued that tinkering and technical skills are skills engineers bring to the practice of engineering. Four items encompassed engineering design skills. "The engineering design process is a central theme in the engineering profession and essentially all engineering curricula" (Schubert et al., 2012, p. 177). Carberry et al. (2010) presented the engineering design process as a multi-step process. Each step in the design process requires skills specific to the engineering design tasks including decision making and the application of basic sciences, mathematics, and engineering sciences.

Achievement goal orientation. The Achievement Goal Orientation Scale, adapted from Harackiewicz et al. (2000), was used to assess students' self-reported adoption of mastery and performance approach goals in their engineering coursework. This scale was developed for use in college classes. The items in the scale (see Appendix D) are comparable to the PALS' mastery and performance approach subscales developed by Midgley et al. (2000). Items from the performance avoidance subscale of PALS were possible in my engineering classes," and "The most important thing for me is trying to understand the content in my engineering classes as thoroughly as possible." Performance goals were assessed with items such as, "My goal in my engineering classes is to do well compared to other engineering students in my program," and "Getting good grades in my engineering classes is the most important thing for me right now."

Performance avoidance goal items included statements such as, “One of my goals in my engineering class is to avoid looking like I have trouble doing the work.” The Cronbach’s alphas for each scale are as follows: mastery goal items (α = .85), performance goal items (α = .89), and performance avoidance goal items (α = .74).

Task value. Most of the items in the task value scale were taken from the instrument measuring general perspectives about engineering developed by Li et al. (2008). Items in this instrument (see Appendix E) are based on expectancy-value theory (Eccles & Wigfield, 2002) and assess students’ perceptions of attainment value, intrinsic value, utility value, and cost associated with completing tasks in engineering. Intrinsic value items included statements such as, “I like engineering design projects,” whereas cost items included statements like, “Engineering is a tough program.” The Cronbach’s alphas obtained by Li et al. (2008) for the scores on intrinsic value was .93 and on perceived cost was .82. Due to the low reliabilities obtained by Li et al. for the utility value item scores (α ranged from .58 to .69), I created four new items to assess utility value. Attainment value items (e.g., “The amount of effort it will take to do well in engineering courses is worthwhile to me”) were adapted from the Self- and Task-Perception Questionnaire (Eccles & Wigfield, 1995) used by Jones et al. (2010) in their study on engineering students’ motivation. The Cronbach’s alpha for the attainment scale was .71.

Intent to persist in engineering. The items in the scales measuring intentions to persist in engineering were modifications of the items in the Persistence in Engineering (PIE) survey developed by Eris et al. (2010). The PIE survey was intended to identify correlates of persistence in engineering. It explores two levels of persistence, namely, academic and professional persistence. In this dissertation study, intent to pursue an engineering degree and intent to pursue engineering as a career were used as proxies for academic persistence and professional persistence in engineering, respectively (Concannon & Barrow, 2010; Eris et al., 2010). Intent to pursue an engineering degree was operationalized with two items assessing a) students' intention to enroll in engineering courses in their major and b) students' intention to complete all requirements to obtain their engineering degree. Intent to persist in one's engineering major (academic persistence) was assessed with the following two items: "I intend to enroll in engineering courses next semester" and "I intend to complete all requirements for my engineering degree program." The correlation for these items is r (222) = .36, $p < .001$.

Intent to pursue engineering as a career is operationalized as students' intention to either practice engineering or conduct research in engineering. The original items in the PIE survey were phrased as questions: "Do you intend to complete a major in engineering?" and "Do you intend to practice, conduct research in, or teach engineering for at least three years after graduating?" The second question asked about intentions to pursue at least one of the three possible options after graduation. In this dissertation study, I crafted items (see Appendix F) as statements to which students responded using a 6-point Likert-type response scale (1 = *strongly disagree*; 6 = *strongly agree*). Professional persistence was assessed by these two items: "I intend to practice engineering for at least 3 years after I graduate" and "I intend to conduct research in engineering for at least 3 years after I graduate." The correlation for these items is r (222) = .25, $p < .001$.

Academic Achievement. Students' ACT mathematics scores were included as a predictor variable in the study. Some students only had SAT mathematics scores (n = 11) and these were converted to ACT mathematics scores based on concordance tables (Dorans, 1999). ACT mathematics scores ranged from 17 to 36 (M = 29.06, SD = 4.25).

Two grade point averages were used as outcomes in this study: engineering core GPA and engineering major GPA. Students' grades were obtained from their transcripts with the permission of the university registrar's office. To compute for grade point averages, I followed the procedure used by Jones et al. (2010). Grade point averages were calculated by multiplying each course grade (i.e., A = 4.0, B = 3.0. C = 2.0, D = 1.0, and E = 0.0) by the number of credits for each course, and then I averaged the sum of these values for all of the students' courses.

Students' engineering core GPA was calculated based on grades that they have received in their engineering-related courses that are typically taken in the first two years of their engineering program and are common to engineering students regardless of their major. These engineering-related courses were considered to be prerequisites for engineering major courses. I did not choose overall GPA as this would include non-engineering-related courses, such as Humanities courses or electives. I wanted to examine their achievement specific to engineering. I included available grades in thirteen engineering core courses: General College Chemistry I and II, and Laboratory to Accompany General Chemistry I; Calculus I, II, III, and IV; two courses in General University Physics and the accompanying laboratory courses; First Course in Computer Science for Engineers, and an engineering mechanics course (i.e., Statics). The engineering core GPA for some students was based on fewer than the thirteen courses listed because these students may have taken Advanced Placement (AP) or transfer credit for one or more of these courses.

A similar procedure was used to calculate for engineering major GPA. Due to the varying year levels of students in the study, I included students' grades from engineering courses that were specific to engineering majors, and then multiplied the grade point for the course by the number of credits for the course and averaged the sum of these values for all of the students' courses. Engineering GPAs were calculated to match the engineering self-efficacy measures in this study.

Data Analysis

Data collected through Qualtrics was exported to IBM SPSS Statistics version 21.0 for analysis. Before conducting analyses, data were checked for errors and cleaned. Cases were excluded on a pairwise basis, i.e., student's data were excluded only for analyses for which student has missing data, such as no ACT or SAT mathematics score (n = 35), no core GPA due to transfer of credit units (n = 26), or no major GPA (n = 14). I conducted exploratory, descriptive analyses of all data by examining item means, standard deviations, frequency distributions, histograms, outliers, skewness, and kurtosis (Seltman, 2013). I checked for outliers by inspecting boxplots with identified outliers. For items with identified outliers, I compared the original mean with the 5% trimmed mean to see if the outliers' scores led to a significant difference in the two mean values (Pallant, 2010). I calculated z scores to identify univariate outliers for all the engineering self-efficacy scales. Fewer than 5% of the z scores had values greater than 1.96, only 1% of the z scores had values greater than 2.58; a few cases were above 3.29. The percentages obtained were consistent with what is expected in a normal distribution.

Absolute values of skewness and kurtosis were within the criteria recommended by Kline (1998) for determining normal distributions. In addition, I compared the original mean with the 5% trimmed mean to determine the influence of outliers. Because the two mean values were not too different from the remaining distribution, all outliers were retained in the data and included in the analyses.

To detect multivariate outliers, I followed Tabachnick and Fidell's (2013) guidelines. I computed the Mahalanobis distance for each case, determined the critical chi-square value (i.e., 18.47), and then evaluated the Mahalanobis distance values against the critical value. One multivariate outlier was found with a Mahalanobis distance of 19.44. I then checked the value for Cook's distance to determine if a particular outlier would be problematic. According to Tabachnick and Fidell, cases with values larger than 1.0 are a potential problem. The maximum value for Cook's distance was less than 1.0, suggesting no major problems. Thus, the multivariate outlier was included in subsequent analyses.

Psychometric properties of engineering self-efficacy scales. The first objective of my study was to examine the psychometric properties of the measures designed to assess general engineering self-efficacy and engineering skills self-efficacy. Given an initial pool of items for each engineering self-efficacy measure (six items for the general engineering self-efficacy scale and 21 items for the engineering skills self-efficacy scale), I needed to determine if all the items in their respective scales were necessary to measure the corresponding type of engineering self-efficacy. DeVellis (1991) commented that "the more items you have in your pool, the fussier you can be about choosing which ones will do the job you intend" (p. 57). My goal is to have reliable, parsimonious scales with items that reflect the construct of engineering self-efficacy.

Therefore to determine which items to flag for possible elimination, I used three screening methods. First, I explored each item to see if responses were normally distributed. I followed Kline's (1998) recommended criteria for determining normal distributions; skewness with an absolute value greater than 3.0 and kurtosis with an absolute value greater than 10.0 indicate a serious deviation from normality. Second, I examined the correlation between the items to justify retaining the items in the scale. The higher the correlations among items, the more reliable the items on the scale, and this makes the scale itself more reliable (DeVellis, 1991). Third, I examined the corrected item-scale correlations to check that each item correlated substantially with the rest of the items in each respective scales. A minimum corrected item-total correlation of .30 with the total score is considered desirable (DeVellis, 1991; Field, 2013). An item with a high item-scale correlation is more desirable than an item with a low value (DeVellis, 1991). Items with extremely low correlations with other items in the scale were flagged for removal. I took note of the flagged items and the reason they were flagged to later decide whether to retain each item for further analyses. Elimination of an item from further analyses depended on the number of flags it received.

Next, I examined the Cronbach's alpha coefficients for the retained items in each scale. The alpha coefficient is one of the most important indicators of a scale's quality and provides an indication of how well different items in the scales fit together in the scale (i.e., internal consistency) (DeVellis, 1991). As a rule of thumb, Cronbach's alpha should be above .70 to ensure that the items in a single scale are related enough to warrant their combination into that scale (DeVellis, 1991; Pearson, 2010).

Items were next subjected to exploratory factor analysis (EFA) to determine their factor structure (Field, 2013; Thompson, 2004). Two separate EFAs were conducted: one for the general engineering self-efficacy items and one for the engineering skills self-efficacy items. I examined Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. A KMO value greater than .50 indicates that a factor analysis is appropriate for use with the data (Cerny & Kaiser, 1977; Field, 2013). Bartlett's test of sphericity was also used to check whether every item was correlated adequately with all the other items for factor analyses to be conducted (Field, 2013). The test should be significant ($p < .05$), as this would indicate that the variables are correlated (Field, 2013).

Next, I used the appropriate factor extraction method depending on the normality of the data (i.e., maximum likelihood for normal distribution or principal axis factoring for significantly non-normal distribution). To determine the number of factors to retain, I used the Kaiser criterion of eigenvalues greater than 1.0 (Kaiser, 1970). I also examined the scree plot of eigenvalues associated with each factor and determined where the discontinuity of the eigenvalue occurs (Gorsuch, 1983; Tabachnick & Fidell, 2013). Thompson (2004) suggested that factor extraction be stopped at the point where there is an "elbow," or leveling of the plot. I also examined the factor loadings for each item. The significance of a factor loading depends on sample size. For a sample size of 100, a factor loading greater than .50 is recommended to be significant (Stevens, 2002). Some researchers have recommended a factor loading greater than .30 for an item to be of substantive importance to a factor (Field, 2013). Given the exploratory nature of my study, I considered using .30 as an acceptable factor loading.

I used factor rotation to transform the factor matrix into a simpler one that is easier to interpret, keeping in mind that factor rotation is not possible if the scale is unidimensional (Thompson, 2004). Because the factors were correlated, an oblique rotation was a suitable method (Osborne, Costello, & Kellow, 2008). I then followed Pett, Lackey, and Sullivan's (2003) suggestion to refine the factors generated in the factor analysis by evaluating the loadings in the factor structure matrix. I took note of those items with loadings less than .40 and items that loaded on multiple factors. If an item was removed from the scale, the scale was factor analyzed again.

Reliability and validity. After conducting each EFA, I once again computed Cronbach's alpha coefficients for the items in each scale to measure each scale's reliability (DeVellis, 1991; Field, 2013). Evidence for content validity was established by asking a panel of experts to review the items in the scales. I examined concurrent and predictive validity by analyzing bivariate correlations among the study variables. Concurrent validity was determined by checking the extent to which engineering self-efficacy scores were related to achievement goal orientations and task value. To determine predictive validity, I examined correlations among engineering self-efficacy, and academic achievement (engineering core GPA and engineering major GPA).

Mean differences. Prior to investigating mean differences between groups, I calculated the scale scores for each self-efficacy scale by taking the mean of the items that make up each scale. I conducted a three-way multivariate analysis of variance (MANOVA) to explore mean differences in the four types of self-efficacy by gender, year level, and major. The independent variables were gender (i.e., male, female), year level (i.e., upperclassmen, lowerclassmen), and major (i.e., biosystems, chemical and materials, civil, electrical and computer, and mechanical engineering). The dependent variables were the four types of engineering self-efficacy (i.e., general engineering self-efficacy, research skills self-efficacy, tinkering skills self-efficacy, and engineering design self-efficacy). Conducting a series of analyses of variance (ANOVA) separately for each dependent variable increases the risk of an inflated Type 1 error, meaning significant results may be found even when there are no differences between the groups (Field, 2013). To reduce the risk of a Type 1 error, MANOVA was conducted. Use of MANOVA is recommended when there is more than one dependent variable and the dependent variables are related in some way (Field, 2013; Pallant, 2010).

I tested whether the data conformed to the assumptions that must be met before conducting the MANOVA. As noted earlier, multivariate normality was checked and met. To assess linearity, I generated matrix scatterplots between each pair of the dependent variables for the groups based on gender, year level, and major. All scatterplots exhibited linear relationships, thus, the assumption of linearity was satisfied. I also checked for multicollinearity between the dependent variables. The types of engineering self-efficacy were moderately correlated. To assess the assumption of homogeneity of variance-covariance matrices, I used the Box's M Test of Equality of Covariance Matrices, which SPSS includes in the MANOVA output. Significant values larger than .001 indicate that the assumption is tenable (Pallant, 2010; Tabachnick & Fidell, 2013). The Box's test was not significant at the alpha = .001 level.

After performing the MANOVA, I examined the significance of Levene's statistic for each dependent variable (significance should be more than .05) to ensure that the assumption of equality of variance was not violated for that variable (Pallant, 2010). Only research skills self-efficacy had a significant value indicating that the assumption of equality of variances for this variable was not met. Tabachnick and Fidell (2013) suggested that if this assumption is violated, a more conservative alpha level for determining significance for that variable should be set when conducting the univariate *F*-test. I therefore used an adjusted alpha of .01.

I checked for multivariate tests of significance using Pillai's Trace. Generally, Wilks' Lambda is most commonly reported; however, due to unequal *N* values and violation of assumptions, Pillai's Trace was more robust (Tabachnick & Fidell, 2013). A significance level of less than .05 implies that there is a difference among the groups (Pallant, 2010).

I conducted a post hoc ANOVA to identify where significant differences lie particularly when the independent variable has three or more levels (e.g., major) (Pallant, 2010). A Bonferroni adjustment (i.e., $\alpha = .05/4$ or $\alpha = .0125$) was applied to account for multiple comparisons among means and to reduce the chance of a Type 1 error (Pallant, 2010; Tabachnick & Fidell, 2013). I only considered results to be significant if the significant value is less than .0125. I also calculated the effect sizes (i.e., Cohen's *d*) to describe the relative magnitude of the differences between groups (Cohen, 1988).

Predictive utility of engineering self-efficacy scales. To investigate the relationships between the dependent variables (engineering GPAs and intentions to persist in engineering) and the independent variables (gender, year-level, major, and ACT mathematics score), I conducted multiple regression with independent variables (predictors) entered in sets or blocks. This type of multiple regression is also called hierarchical or sequential regression (Field, 2013; Pallant, 2010; Tabachnick & Fidell, 2013). I conducted three separate multiple regressions to examine the influence of engineering self-efficacy on three outcomes: engineering core GPA, engineering major GPA, and intent to persist in engineering professionally. Students' scale scores on intent to persist academically were severely skewed and application of data transformation techniques did not result in a normal distribution. I therefore excluded this outcome variable, intent to persist in engineering academically, from further analysis.

For each regression model, the first block of variables entered included gender, year level, major, and ACT math score. Engineering self-efficacy measures (general engineering self-efficacy, research skills self-efficacy, tinkering skills self-efficacy, and engineering design skills self-efficacy) were entered as the second block of variables. Achievement goal orientations (mastery goals, performance goals, and performance avoidance goals) were entered in the third block. The fourth block of variables comprised of task value constructs (intrinsic value, cost, and utility value).

In hierarchical regression, the independent variables are entered into the equation as specified by the researchers (Tabachnick & Fidell, 2013). As a general rule, known predictors (from other research) should be entered in the first block (Field, 2013). Quantitative skills (e.g., ACT or SAT math scores) have been hypothesized to be a predictor of students' success in engineering programs (Veenstra, Dey, & Herrin, 2008; Zhang, Anderson, Ohland, Carter, & Thorndyke, 2004). Thus, ACT math scores were included in the first block. My objective was to investigate the extent to which self-efficacy adds to the prediction of engineering students' achievement (i.e., engineering core GPA and engineering major GPA) and intent to persist in engineering when quantitative skills (i.e., ACT math score) are controlled for. Therefore, four types of engineering self-efficacy were entered in the second block. Then, I included achievement goals and task value in the following blocks to explore whether these added to the explained variance in the outcomes. I also calculated uniqueness indicators using regression commonality analysis to determine the amount of variance explained in the dependent variable by each independent variable (Nathans, Oswald, & Nimon, 2012).

I checked for multicollinearity by scanning the correlation matrix of the predictors making sure that they were not highly correlated ($r \geq .90$). In addition, I examined the VIF statistic, tolerance statistic, and variance proportions (Pallant, 2010). Field (2013) recommended that VIF values should not be greater than 10 and the tolerance statistic should be above .20. The VIF values ranged from 1.04 to 2.39. Tolerance statistics ranged from .42 to .97. All collinearity statistics and diagnostics indicates that there is no concern for multicollinearity. I also calculated structure coefficients because beta weights are sensitive to multicollinearity. Both beta weights and structure coefficients should be interpreted to determine the contribution of predictor variables in the regression (Courville and Thompson, 2001; Kraha, Turner, Nimon, Zientek, & Henson, 2012; Nathans et al., 2012).

Copyright © Natasha Johanna A. Mamaril 2014

Chapter 4: Results

In this chapter, I present the results of the analyses used to address my research questions. First, I present the descriptive statistics for items in the engineering self-efficacy measures and the results of the exploratory factor analyses for the two engineering self-efficacy measures (general engineering self-efficacy and engineering skills self-efficacy). I then describe the psychometric properties of the resulting engineering self-efficacy scales. Second, I report the results of the MANOVA. Third, I present the results of the regression analyses.

Psychometric Properties of Engineering Self-Efficacy Scales

General Engineering Self-Efficacy Scale. All six items in the original general engineering self-efficacy scale were retained based on the items' performance in the scale. Absolute values of skewness and kurtosis were less than 3.0 (see Table 7). Items were correlated substantially with the rest of the items in the scale. Inter-item correlations ranged from .58 to .78, whereas item-total correlations ranged from .76 to .82 (see Table 8).

Table 7

Descriptive Statistics for the General Engineering Self-Efficacy Items

Item	*M*	*SD*	Skewness	Kurtosis
GESE25	4.83	0.84	-0.38	-0.07
GESE26	4.66	0.93	-0.24	-0.47
GESE27	5.12	0.87	-0.93	1.14
GESE28	4.92	0.85	-0.43	-0.45
GESE29	5.16	0.78	-0.53	-0.46
GESE30	4.93	0.92	-0.61	0.28

*N*ote. GESE = General Engineering Self-Efficacy.
$N = 321$

Table 8

Inter-Item and Item-Scale Correlations of General Engineering Self-Efficacy Items

Item	*r*-total	GESE25	GESE26	GESE27	GESE28	GESE29
GESE25	.78					
GESE26	.77	.78				
GESE27	.78	.59	.61			
GESE28	.82	.73	.68	.69		
GESE29	.81	.69	.67	.70	.75	
GESE30	.76	.58	.59	.76	.67	.68

Note. GESE = General Engineering Self-Efficacy.
$N = 321$

The six items of the general engineering self-efficacy scale were then subjected to exploratory factor analysis (EFA). Prior to performing EFA, the suitability for factor analyses was assessed. The Kaiser-Meyer-Olkin (KMO) value was .90, exceeding the recommended value of .60 (Cerny & Kaiser, 1977). A KMO value close to 1.0 indicates that patterns of correlations are relatively compact and factor analysis should yield distinct and reliable factors (Field, 2013). Bartlett's test of sphericity reached statistical significance, indicating that relationships exist among the items and that factor analyses can be used with the data. The maximum-likelihood extraction method resulted in one factor with an eigenvalue of 4.75, explaining 67.83% of the variance. The unidimensionality of the scale was further supported by the clear break on the scree plot. Table 9 shows the factor loadings and communalities for the six items.

Table 9

Final Factor Loadings and Communalities for Exploratory Factor Analysis of the General Engineering Self-Efficacy Items

Item	GESE	h^2
1. I can master the content in the engineering-related courses I am taking this semester.	.82	.67
2. I can master the content in even the most challenging engineering course if I try.	.80	.65
3. I can do a good job on almost all my engineering coursework if I do not give up.	.81	.65
4. I can do an excellent job on engineering-related problems and tasks assigned this semester.	.87	.75
5. I can learn the content taught in my engineering-related courses.	.85	.73
6. I can earn a good grade in my engineering-related courses.	.79	.62
Percentage of variance	67.73%	

Note. GESE = General Engineering Self-Efficacy. h^2 = communality.

Engineering Skills Self-Efficacy Scale. Two items in the original engineering skills self-efficacy scale were removed due to their similar wording to two general engineering self-efficacy items. The items, "I can learn academic subject matter in engineering" (ESSE23), and "I can master engineering subject matter" (ESSE25), were similar to "I can learn the content taught in engineering-related courses" (GESE29) and "I can master the content in the engineering-related courses I am taking this semester" (GESE25), respectively.

After examining the descriptive statistics, I flagged one item, "I can build machines" (ESSE10), on the original engineering skills self-efficacy scale because it had an inter-item correlation less than .30. However, after checking the item-total correlation

(.70), I decided to keep the item. The removal of two items from the engineering skills self-efficacy scale resulted in 19 items.

An EFA was conducted on the 19 items using maximum-likelihood extraction with oblique rotation (Promax). The KMO measure verified the sampling adequacy for the analysis, KMO = .93. Bartlett's test of sphericity was significant, indicating that the variables are correlated and justifying the use of factor analysis. An initial analysis was run to obtain eigenvalues for each factor. Four factors had eigenvalues over 1.0, accounting for 54.93%, 9.58%, 6.23%, and 4.57% of the variance, respectively. However, Kaiser's criterion of retaining factors with eigenvalues greater than 1.0 often overestimates the number of factors (Field, 2013). The scree plot was ambiguous and showed inflexions that would justify retaining either two or three factors.

Because of the unclear cutoff for the number of factors, I undertook several factor analyses with different numbers of specified factors (i.e., two, three, or four) as suggested by Tabachnick and Fidell (2013). Preacher, Zhang, Kim, and Mels (2013) suggested searching for the best number of factors to retain to satisfy the researcher's goal. In this dissertation study, the primary goal is to retain factors adequate for descriptive and predictive purposes. In the two-factor solution, several items cross-loaded on the factors. In the four-factor solution, some items also loaded on two or more factors. I then examined whether the four-factor solution made sense conceptually compared to a three-factor solution. Two factors were common to the three- and four-factor solutions (i.e., engineering research skills self-efficacy and engineering design self-efficacy). One factor in the three-factor solution (i.e., tinkering skills self-efficacy) was split into two factors in the four-factor solution (i.e., tinkering skills self-efficacy items being separated as tool-related versus machine-related). In the three-factor solution, the items loaded strongly onto the hypothesized factor of tinkering skills self-efficacy. A three-factor solution made the most sense empirically and theoretically, demonstrating a balance between good fit to data and model parsimony (Preacher et al., 2013).

After rotating the three-factor solution, I examined the pattern matrix and interpreted variables with loadings of .30 or higher (Tabachnick & Fidell, 2013). Worthington and Whittaker (2006) suggested removing items that cross-loaded when the factor loadings on two factors differed by less than .15. Two items, "I can design new things" (ESSE7) and "I can apply technical concepts in engineering" (ESSE24), cross-loaded. These items were removed from the analyses one at a time, and data were analyzed again as recommended by Pett et al. (2003).

After factor extraction and rotation, 17 items remained in a three-factor solution. The items that clustered on Factor 1 represent engineering research skills self-efficacy (5 items), Factor 2 represents tinkering skills self-efficacy (8 items), and Factor 3 represents engineering design skills self-efficacy (4 items). Worthington and Whittaker (2006) suggested optimizing the scale length only after the factor solution is clear. Optimizing scale length involved assessing the trade-off between length and reliability. Upon review of the items for each factor, I noted that the tinkering skills self-efficacy subscale had more items than the other scales. To balance the number of items for each factor, I decided to remove three items from the tinkering skills self-efficacy scale. "I can work with tools and use them to build things" (ESSE5) and "I can work with tools and use them to fix things" (ESSE6) were removed because these items appeared to be covered already by "I can assemble things" (ESSE22) and "I can disassemble things" (ESSE26).

I also removed "I can fix machines" (ESSE11) because it was highly correlated (r = .90) with a similar item, "I can build machines" (ESSE10). Removal of these three items resulted in 14 skills self-efficacy items: 5 items measuring research skills self-efficacy, 5 items measuring tinkering self-efficacy, and 4 items measuring engineering design self-efficacy. An EFA was conducted with the final 14 items. Means, standard deviations, skewness, kurtosis, inter-item, and item-total correlations for the items in each engineering skills self-efficacy scales are presented in Tables 10 and 11.

Table 10

Descriptive Statistics for the Engineering Skills Self-Efficacy Items

Item	*M*	*SD*	Skewness	Kurtosis
ESSE1	4.69	0.96	-0.43	-0.21
ESSE2	4.89	0.83	-0.35	-0.32
ESSE3	4.93	0.92	-0.74	0.40
ESSE4	4.96	0.88	-0.59	-0.02
ESSE8	4.93	0.91	-0.60	-0.12
ESSE9	4.85	1.05	-0.69	0.00
ESSE10	4.06	1.33	-0.19	-0.70
ESSE13	4.79	0.96	-0.54	-0.07
ESSE15	4.71	0.97	-0.64	0.43
ESSE18	4.81	0.94	-0.67	0.41
ESSE20	4.76	0.97	-0.55	0.02
ESSE21	4.45	1.12	-0.38	-0.29
ESSE22	5.10	0.96	-0.98	0.61
ESSE26	5.23	0.92	-1.18	1.18

Note. ESSE = Engineering Skills Self-Efficacy.
N = 321

Table 11

Inter-Item and Item-Scale Correlations of Engineering Skills Self-Efficacy Items

Item	*r*-total	ESSE1	ESSE2	ESSE3	ESSE4	ESSE8	ESSE9	ESSE10	ESSE13	ESSE15	ESSE18	ESSE20	ESSE21	ESSE22	ESSE26
ESSE1	.67														
ESSE2	.69	.76													
ESSE3	.60	.50	.63												
ESSE4	.53	.46	.62	.68											
ESSE8	.57	.49	.57	.37	.40										
ESSE9	.79	.57	.48	.45	.36	.53									
ESSE10	.66	.42	.33	.30	**.19**	.31	.70								
ESSE13	.78	.48	.51	.47	.41	.39	.59	.57							
ESSE15	.79	.50	.50	.48	.41	.44	.60	.57	.86						
ESSE18	.76	.49	.50	.38	.40	.48	.58	.54	.82	.82					
ESSE20	.78	.51	.53	.45	.40	.41	.57	.55	.79	.85	.85				
ESSE21	.69	.47	.44	.36	**.27**	.48	.66	.68	.58	.55	.53	.53			
ESSE22	.73	.45	.45	.44	.36	.35	.71	.64	.55	.57	.51	.55	.55		
ESSE26	.67	.43	.48	.42	.41	.35	.68	.54	.46	.44	.43	.48	.53	.83	

Note. ESSE = Engineering Skills Self-Efficacy. *r*-total is the correlation between a particular item and the total scale. All correlations were significant at the $p < .01$ level. Values < .30 are bolded.
$N = 321$

Table 12 shows the final factor loadings and communalities of the engineering skills self-efficacy items. Pattern loadings ranged from .40 to .88 on research skills self-efficacy, .48 to .94 on tinkering skills self-efficacy, and .85 to .91 on engineering design self-efficacy.

Table 12

Final Factor Pattern Loadings and Communalities for Exploratory Factor Analysis of the Engineering Skills Self-Efficacy Items

Item	Research Skills SE	Tinkering Skills SE	Engineering Design SE	h^2
1. I can perform experiments independently.	.65			.57
2. I can analyze data resulting from experiments.	.88			.78
3. I can orally communicate results of experiments.	.72			.56
4. I can communicate results of experiments in written form.	.77			.55
5. I can solve problems using a computer.	.40			.39
6. I can work with machines.		.68		.69
7. I can build machines.		.56		.57
8. I can manipulate components and devices.		.48		.50
9. I can assemble things.		.93		.84
10. I can disassemble things.		.94		.80
11. I can identify a design need.			.87	.82
12. I can develop design solutions.			.91	.86
13. I can evaluate a design.			.91	.82
14. I can recognize changes needed for a design solution to work.			.85	.82
Percentage of variance	8.45%	7.24%	52.62%	68.32%

Note. SE = Self-Efficacy. Factor loadings > .40 are shown. h^2 = communality.

Reliability and validity. Following the factor analyses, I computed for Cronbach's alpha coefficients to estimate internal consistency. As presented in Table 13, the alpha coefficients for the engineering self-efficacy scales are robust. They ranged from .86 to .95, indicating good internal consistency.

Table 13

Cronbach's Alpha Coefficients for the Engineering Self-Efficacy Items

Scale	α
General Engineering Self-Efficacy	.93
Experiment/Research Skills Self-Efficacy	.86
Tinkering Skills Self-Efficacy	.90
Engineering Design Self-Efficacy	.95

To examine concurrent validity, I analyzed bivariate correlations among the engineering self-efficacy scales and related motivation constructs, specifically achievement goals and task values. Bivariate correlations are found in Table 14. As expected, the different engineering self-efficacy measures were positively related to one another. All correlations between self-efficacy variables were significant at the .01 level.

The four engineering self-efficacy measures were significantly correlated to mastery goals at $p < .01$. Only general engineering self-efficacy and research skills self-efficacy were significantly correlated to performance goals. There was no significant relationship between any of the four types of engineering self-efficacy and performance avoidance goals.

All four types of engineering self-efficacy were positively related to both intrinsic value and utility value. Correlations between the self-efficacy and intrinsic value and utility value were significant. Perceived cost was negatively related to general engineering self-efficacy but unrelated to skills self-efficacy.

Table 14

Means, Standard Deviations, and Bivariate Correlations for Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. General Engineering SE															
2. Research Skills SE	.50**														
3. Tinkering Skills SE	.30**	.59**													
4. Engineering Design Skills SE	.35**	.61**	.68**												
5. Mastery Goals	.45**	.45**	.32**	.47**											
6. Performance Goals	.19**	.13*	.01	.11	.29**										
7. Performance Avoidance Goals	-.11	-.12	-.05	.03	.10	.44**									
8. Intrinsic Value	.37**	.45**	.40**	.45**	.59**	.23**	.12								
9. Cost	-.17*	.07	-.01	.06	.21**	.18**	.06	.20**							
10. Utility Value	.14*	.21**	.18**	.22**	.26**	.08	-.01	.35**	.39**						
11. ACT Math Score	.24**	.08	-.13	-.12	-.05	.12	.03	-.04	-.15*	-.12					
12. Engineering Core GPA	.33**	.08	-.18*	-.03	.03	.08	-.12	-.09	-.12	-.04	.57**				
13. Engineering Major GPA	.38**	.12	-.10	-.07	.09	.20**	-.10	.02	-.11	-.05	.44**	.62**			
14. Intent to persist professionally	.12	.04	-	.07	.23**	.08	.11	.36**	-.02	-.03	.06	-.04	.06		
15. Intent to persist academically (transformed)	-.03	.01	-.01	-	-.13	-.06	-.05	-.04	-.06	-.04	-.08	.06	-.04	-.30**	
16. Gender	-.07	-.01	-.02	-	-.01	-.02	.07	-.10	.01	-.01	.12	.10	.04	-.08	-.06
M	4.95	4.88	4.78	4.77	5.12	4.49	3.73	5.07	5.31	5.29	29.06	3.11	3.30	4.24	0.10
SD	0.75	0.74	0.92	0.90	0.61	1.05	1.28	0.68	0.71	0.56	4.25	0.69	0.59	1.07	0.19

Note. SE = Self-Efficacy. GPA = Grade Point Average. Scores on intent to persist in engineering academically were transformed because they were severely negatively skewed.

*$p < .05$, ** $p < .01$

$N = 224$

Correlations with measures of academic performance (i.e., engineering core GPA and engineering major GPA) were examined to provide evidence of predictive validity of the engineering self-efficacy scales. As shown in Table 14, general engineering self-efficacy was significantly and positively correlated with both GPA outcomes. Tinkering skills self-efficacy was significantly and negatively related to engineering core GPA. I also examined the bivariate correlations among each engineering self-efficacy measures, and students' intentions to persist in engineering professionally. None of the engineering self-efficacy measures was significantly correlated with intentions to persist.

Mean Differences in Types of Engineering Self-Efficacy

Means and standard deviations of the four types of engineering self-efficacy for the full sample, by gender, by year level, and by major, are found in Table 15. A three-way multivariate analysis of variance was conducted to investigate mean differences in engineering self-efficacy. Table 16 presents the MANOVA results. Using Pillai's trace, there was a significant difference in engineering self-efficacy as a function of major, V = 0.151, $F(4, 179) = 1.781$, $p = .03$. A separate one-way ANOVA on engineering self-efficacy revealed a significant mean difference in tinkering self-efficacy, $F(4, 196) = 5.14$, $p < .01$ (see Table 17). Post hoc comparisons using the Bonferroni adjusted alpha level of .0125 showed that the average tinkering skills self- efficacy score of mechanical engineering majors ($M = 5.10$, $SD = 0.85$) was significantly higher than that of chemical and materials engineering majors ($M = 4.30$, $SD = 0.69$). The mean comparisons among majors' tinkering skills self-efficacy are presented in Table 18. Mean levels did not differ for any other type of self-efficacy belief as a function of students' major.

Table 15

Means and Standard Deviations of Engineering Self-Efficacy Scores

	General Engineering SE *M* (*SD*)	Research Skills SE *M* (*SD*)	Tinkering Skills SE *M* (*SD*)	Engineering Design SE *M* (*SD*)
Full Sample				
(*N* = 224)	4.95 (0.75)	4.88 (0.74)	4.78 (0.92)	4.77 (0.90)
Gender				
Men (*n* = 171)	4.99 (0.74)	4.89 (0.73)	4.79 (0.94)	4.76 (0.90)
Women (*n* = 53)	4.85 (0.79)	4.88 (0.77)	4.74 (0.86)	4.77 (0.89)
Year Level				
Lowerclassmen (*n* = 68)	5.03 (0.76)	4.83 (0.74)	4.77 (0.92)	4.69 (0.89)
Upperclassmen (*n* = 156)	4.91 (0.75)	4.91 (0.74)	4.77 (0.94)	4.80 (0.90)
Major				
Biosystems Engineering (*n* = 25)	4.89 (0.61)	4.77 (0.73)	4.69 (0.90)	4.54 (0.98)
Chemical and Materials Engineering (*n* = 31)	4.81 (0.90)	5.02 (0.69)	4.30 (0.69)	4.62 (0.76)
Civil Engineering (*n* = 57)	4.99 (0.72)	4.84 (0.79)	4.66 (0.95)	4.77 (0.81)
Electrical and Computer Engineering (*n* = 27)	5.14 (0.78)	5.05 (0.71)	4.99 (0.95)	4.94 (0.89)
Mechanical Engineering (*n* = 61)	4.91 (0.77)	4.89 (0.74)	5.10 (0.85)	4.85 (0.95)

Note. SE = Self-Efficacy. Corresponding standard deviations are in parentheses.
*p < .01

Table 16

Three-Way Multivariate Analysis of Variance Results

Variable	Pillai's Trace (V)	*F*	*p*
Gender	.005	0.205	.936
Year Level	.033	1.507	.202
Major	.151	1.781	.030*
Gender*Year Level	.024	1.104	.356
Gender*Major	.051	0.590	.892
Year Level*Major	.098	1.148	.306
Gender*Year Level*Major	.023	0.352	.979

*p < .05

Table 17

One-Way Analysis of Variance Results for Engineering Skills Self-Efficacy by Major

Variable	*F*	*p*
General Engineering Self-Efficacy	0.807	.522
Research Skills Self-Efficacy	0.788	.534
Tinkering Skills Self-Efficacy	5.14	.001*
Engineering Design Self-Efficacy	1.040	.388

*p < .01

Table 18

Mean Differences in Tinkering Skills Self-Efficacy by Major

Major		Mean Difference	Cohen's *d*
Mechanical vs.	Biosystems	0.42	0.48
Mechanical vs.	Chemical and Materials	0.81*	1.01
Mechanical vs.	Civil	0.45	0.49
Mechanical vs.	Electrical and Computer	0.12	0.13

Note. A positive mean difference indicates that mean for majors on the left is higher than mean for majors on the right. Post hoc analyses using adjusted Bonferroni criterion for significance.
*p < .01

Predictive Utility of Engineering Self-Efficacy Scales

Engineering Self-Efficacy and Engineering Core GPA. Results of the multiple regression showed that engineering self-efficacy was a significant predictor of engineering core GPA, $F(8, 162) = 14.39$, $p < .01$, and explained an additional 9% of the variance of the outcome variable after controlling for ACT mathematics score (see Table 19). As shown in Step 2 of the model, general engineering self-efficacy was positively related to engineering core GPA, whereas tinkering skills self-efficacy was negatively related to engineering core GPA. Commonality analysis results demonstrated that general engineering self-efficacy contributed the most unique variance (10.64%) to engineering core GPA, followed by tinkering skills self-efficacy (10.08%), and engineering design self-efficacy (2.22%) in Step 2 of the model. In Step 3 and Step 4, general engineering self-efficacy, tinkering skills self-efficacy, and engineering design self-efficacy significantly contributed to the prediction of engineering core GPA. Research skills self-efficacy did not contribute to the variance explained in engineering core GPA. Achievement goals and task value were unrelated with engineering core GPA and their addition to the model did not explain a significant proportion of the variance for this outcome.

Table 19

Hierarchical Regression Analyses Predicting Engineering Core GPA

Predictor	Step 1	Step 2	Step 3	Step 4
Gender (β)	.03	.06	.07	.06
Year Level (β)	.00	.01	-.02	-.02
Major (β)	-.01	.05	.04	.06
ACT Math Score (β)	.57**	.48**	.48**	.48**
Structure Coefficient	.99	.89	.87	.85
Uniqueness	95.05%	46.33%	43.25%	40.49%
General Engineering Self-Efficacy (β)		.25**	.24**	.25**
Structure Coefficient		.51	.50	.49
Uniqueness		10.64%	8.04%	7.21%
Research Skills Self-Efficacy (β)		.01	-.02	.01
Structure Coefficient		.12	.12	.12
Uniqueness		0%	0%	0%
Tinkering Skills Self-Efficacy (β)		-.31**	-.31**	-.30**
Structure Coefficient		-.28	-.27	-.27
Uniqueness		10.08%	9.54%	8.42%
Engineering Design Skills Self-Efficacy (β)		.14	.18*	.19*
Structure Coefficient		-.04	-.04	-.04
Uniqueness		2.22%	3.20%	3.36%
Mastery Goals (β)			-.03	.03
Structure Coefficient			.05	.05
Uniqueness			0%	0%
Performance Goals (β)			.04	.05
Structure Coefficient			.13	.12
Uniqueness			0%	0%
Performance Avoidance Goals (β)			-.16	-.14*
Structure Coefficient			-.19	-.19
Uniqueness			4.06%	3.11%
Intrinsic Value (β)				-.16
Structure Coefficient				-.13
Uniqueness				2.94%
Cost (β)				-.01
Structure Coefficient				-.18
Uniqueness				0%
Utility Value (β)				.03
Structure Coefficient				-.06
Uniqueness				0%
F	20.31**	14.39**	11.13**	9.06**
Model R^2	.33	.42	.44	.45
R^2 Change	.33**	.09**	.02	.01

Note. *$p < .05$, **$p < .01$

Engineering Self-Efficacy and Engineering Major GPA. Results of the hierarchical multiple regression showed that engineering self-efficacy predicted engineering major GPA, $F(8, 162) = 8.63$, $p < .01$, and explained an additional 10% of the variance in the achievement outcome when ACT mathematics score was controlled (see Table 20). Commonality analysis results showed that general engineering self-efficacy contributed the most unique variance (27.55%) to engineering major GPA, compared to tinkering skills self-efficacy (2.97%) and engineering design self-efficacy (1.32%) when entered in Step 2. The addition of achievement goals and task value in Step3 and Step 4, respectively, did not contribute to the variance explained in engineering major GPA. General engineering self-efficacy contributed significantly to the prediction of engineering major GPA even when achievement goals and task value were in the model.

Table 20

Hierarchical Regression Analyses Predicting Engineering Major GPA

Predictor	Step 1	Step 2	Step 3	Step 4
Gender (β)	-.02	.02	.04	.04
Year Level (β)	-.04	-.02	-.03	-.03
Major (β)	-.04	.00	-.01	.00
ACT Math Score (β)	.44**	.32**	.31**	.31**
Structure Coefficient	.99	.80	.76	.76
Uniqueness	94.50%	27.57%	23.96%	22.15%
General Engineering Self-Efficacy (β)		.35**	.31**	.30**
Structure Coefficient		.69	.66	.66
Uniqueness		27.55%	17.10%	14.26%
Research Skills Self-Efficacy (β)		.06	.02	.03
Structure Coefficient		.21	.20	.20
Uniqueness		0%	0%	0%
Tinkering Skills Self-Efficacy (β)		-.14	-.12	-.12
Structure Coefficient		-.19	-.18	-.18
Uniqueness		2.97%	1.82%	1.86%
Engineering Design Skills Self-Efficacy (β)		-.09	-.08	-.08
Structure Coefficient		-.13	-.12	-.12
Uniqueness		1.32%	0%	0%
Mastery Goals (β)			.00	.02
Structure Coefficient			.16	.16
Uniqueness			0%	0%
Performance Goals (β)			.18*	.19*
Structure Coefficient			.35	.35
Uniqueness			7.28%	7.53%
Performance Avoidance Goals (β)			-.17*	-.17*
Structure Coefficient			-.18	-.17
Uniqueness			5.98%	5.86%
Intrinsic Value (β)				-.02
Structure Coefficient				.04
Uniqueness				0%
Cost (β)				-.03
Structure Coefficient				-.19
Uniqueness				0%
Utility Value (β)				-.03
Structure Coefficient				-.08
Uniqueness				0%
F	10.05**	8.63**	7.08**	5.52**
Model R^2	.20	.30	.33	.33
R^2 Change	.20**	.10**	.03	.00

Note. *$p < .05$, **$p < .01$

Engineering Self-Efficacy and Intent to Persist in Engineering. The results of the third hierarchical regression analyses with intent to persist in engineering professionally as the outcome are presented in Table 21. In Step 2 of the model, the addition of engineering self-efficacy to the equation did not improve the R^2. In Step 3 of the model, the addition of achievement goals did not contribute to the variance explained in interest to persist in engineering. Neither engineering self-efficacy nor achievement goals was a significant predictor of students' intent to persist. In Step 4 of the model, the addition of task value resulted in a significant change in R^2. Task value explained 21% of the variance in students' intent to persist in engineering. Specifically, intrinsic value was a significant predictor of intentions to persist in engineering. Commonality analysis revealed that intrinsic value contributed a unique variance (54.84%) to this outcome variable.

Table 21

Hierarchical Regression Analyses Predicting Intent to Persist in Engineering

Predictor	Step 1	Step 2	Step 3	Step 4
Gender (β)	-.09	-.08	-.09	-.05
Year Level (β)	-.12	-.12	-.08	-.06
Major (β)	-.02	-.02	-.01	-.04
ACT Math Score (β)	.06	.04	.07	.06
Structure Coefficient	.38	.30	.21	.13
Uniqueness	11.30%	2.87%	4.37%	1.41%
General Engineering Self-Efficacy (β)		.09	.03	-.02
Structure Coefficient		.57	.40	.25
Uniqueness		12.65%	0%	0%
Research Skills Self-Efficacy (β)		-.03	-.05	-.10
Structure Coefficient		.20	.14	.09
Uniqueness		0%	1.22%	2.10%
Tinkering Skills Self-Efficacy (β)		-.09	-.07	-.12
Structure Coefficient		-.01	-.01	.00
Uniqueness		9.06%	2.59%	3.02%
Engineering Design Skills Self-Efficacy (β)		.13	.04	.02
Structure Coefficient		.33	.23	.15
Uniqueness		17.87%	0%	0%
Mastery Goals (β)			.24	.10
Structure Coefficient			.79	.51
Uniqueness			41.32%	2.43%
Performance Goals (β)			-.05	-.04
Structure Coefficient			.29	.18
Uniqueness			1.79%	0%
Performance Avoidance Goals (β)			.09	.03
Structure Coefficient			.36	.23
Uniqueness			6.40%	0%
Intrinsic Value (β)				.47**
Structure Coefficient				.80
Uniqueness				54.84%
Cost (β)				-.07
Structure Coefficient				-.05
Uniqueness				1.45%
Utility Value (β)				-.14
Structure Coefficient				-.06
Uniqueness				7.17%
F	1.09	.88	1.37	2.93**
Model R^2	.03	.04	.09	.21**
R^2 Change	.03	.02	.05	.12**

Note. *$p < .05$, **$p < .01$

Summary of Findings

The EFA conducted resulted in a unidimensional general engineering self-efficacy scale that has six items and a multidimensional skills self-efficacy scale with three subscales: engineering research skills self-efficacy (5 items), tinkering skills self-efficacy (5 items), and engineering design self-efficacy (4 items).

Results of a three-way MANOVA showed that women and men did not differ in any of the four types of engineering self-efficacy nor did upperclassmen and lowerclassmen. The hypotheses that men will report higher self-efficacy scores than women and that upperclassmen will report higher scores than lowerclassmen were not supported. A significant difference in self-efficacy scores was found based on students' engineering major. A follow-up one-way ANOVA revealed that engineering students' tinkering self-efficacy differed significantly by student major. Post hoc analyses using a Bonferroni adjustment showed that mechanical engineering majors reported higher self-efficacy than did the students in chemical and materials engineering.

Engineering self-efficacy significantly predicted academic achievement outcomes but not of intent to persist in engineering. Specifically, general engineering self-efficacy and tinkering skills self-efficacy significantly contributed to the prediction of engineering core GPA even when ACT mathematics scores were controlled. General engineering self-efficacy accounted for 28% of the 30% explained variance in engineering major GPA. Intrinsic value significantly predicted intent to persist in engineering professionally and accounted for more than half of the 21% explained variance in this outcome.

Copyright © Natasha Johanna A. Mamaril 2014

Chapter 5: Discussion

I designed this study with three goals in mind. First, I sought to develop and validate items to assess undergraduate students' general engineering self-efficacy and engineering skills self-efficacy. Second, I investigated whether significant mean differences in engineering self-efficacy existed among students based on their gender, year level, and major. Third, I aimed to examine the unique contributions of engineering self-efficacy, achievement goals, and task value to the prediction of achievement outcomes and students' intent to persist in engineering.

Researchers have shown that engineering students' success is linked to scores on the mathematics section of the SAT or the ACT (e.g., Zhang et al., 2004). Clearly, having quantitative skills upon entering engineering programs helps prepare students for the rigors of the engineering curriculum and may help them get through their first year of engineering courses. However, having these skills alone does not ensure that students will be motivated to complete their engineering degrees. Researchers have shown that students' success in engineering lies not only in the number of skills students have, but also in what they believe they can do with these skills. In his social cognitive theory, Bandura (1997) posited that behaviors can often be better predicted by the *beliefs* students hold about their capabilities than by what they have actually accomplished. For this reason, engineering students' beliefs in their abilities to perform engineering tasks could help them function most effectively in their degree programs and motivate them to pursue engineering careers.

Psychometric Properties of Engineering Self-Efficacy Scales

Researchers have used omnibus measures to assess students' self-efficacy in engineering but this presents problems of predictive relevance. At times, the items in these measures assess self-constructs other than self-efficacy. Some researchers have modified existing self-efficacy scales designed for domains other than engineering. They have explored engineering self-efficacy by measuring self-efficacy in engineering-related domains such as mathematics and science. Though these domains are part of the engineering curriculum, experiences unique to engineering exist; thus engineering self-efficacy measures must target performance of activities or tasks relevant to the domain of engineering. Few researchers have captured the different ability beliefs students hold while staying true to Bandura's (1997) definition of self-efficacy. In this study, I developed self-efficacy measures that reflect both general and specific engineering tasks and are closely aligned with Bandura's (2006) guidelines for creating self-efficacy scales.

Despite efforts to craft a self-efficacy scale true to the domain of engineering and to Bandura's (1997) conceptualization of self-efficacy, no scale will ultimately fit all studies of engineering self-efficacy. A self-efficacy scale is not a "one size fits all" measure (Bandura, 2006). Bong (2006) emphasized that the usefulness of self-efficacy scales depends on whether they match the tasks and domain of interest. I referred to existing literature on what engineering researchers, educators, students, and practicing engineers believe to be important skills that engineers should possess. With the help of engineering faculty, I identified tasks that engineering students need to perform in their engineering coursework and in their future roles as engineers. Scale items were worded to assess students' beliefs in their capabilities to perform these engineering tasks.

The results of the exploratory factor analyses supported my hypotheses that the general engineering self-efficacy scale was unidimensional, whereas the engineering skills self-efficacy scale was multidimensional. These findings indicate that engineering self-efficacy can be assessed at two levels: general and task-specific. The general engineering self-efficacy scale measures students' beliefs in their capabilities to perform general tasks associated with academic functioning. Items in this scale were geared toward engineering courses in general yet were content-specific (e.g., mastery of content in engineering), course-specific (e.g., doing assigned engineering work), and grade-specific (e.g., earning a good grade). The engineering skills self-efficacy scale comprised three factors. Five items were related to research skills that ABET specified to be a set of skills graduates of engineering programs should possess. The next five items corresponded to Baker et al.'s (2008) description of tinkering skills. Four items featured *design* as the common element. This result suggests that Carberry et al.'s (2010) engineering design self-efficacy measure can still be reliable with fewer items. These findings provide evidence that students' engineering self-efficacy can be differentiated by the level of specificity of tasks.

Pajares (1996) claimed that the correspondence between the level of task specificity and achievement outcome in the engineering domain is important for a task-specific self-efficacy measure to have explanatory and predictive power. In the field of engineering, few researchers have chosen to match self-efficacy assessments with academic achievement as an outcome measure (e.g., Hsieh et al., 2012). In this dissertation study, I identified engineering GPA as an outcome measure to attain better correspondence with particularized self-efficacy assessments. This outcome was limited, however, as I address later.

The items in the self-efficacy measures developed in this study are consistent with Bandura's (2006) concept of self-efficacy because they are "I can" statements that reflect the construct of self-efficacy, which is a judgment of capability. These items are linked to distinct areas of functioning in the domain of engineering. Moreover, they reflect a level of task demands that represent gradations of challenges to successful performance (Bandura, 2006). Consequently, they offer scholars an improvement over similar engineering self-efficacy scales used in the past that assessed constructs other than self-efficacy (e.g., personality, interest). The general self-efficacy scale and the three engineering skills self-efficacy subscales can be used altogether or separately based on the needs of the researcher or instructor.

Patterns of relationships with other relevant constructs provided support to the validity of the scales. Engineering self-efficacy was positively related to mastery and performance approach goals, and was negatively related to performance avoidance goals. Correlations between the different types of engineering self-efficacy and mastery goals were significant and positive. This result suggests that students with higher self-efficacy tend to strive to develop new skills and acquire knowledge. Conversely, as students learn and master skills, their beliefs in their capabilities to complete engineering tasks successfully likely become stronger. A similar finding was reported by Hsieh et al. (2012).

General engineering self-efficacy and research skills self-efficacy were significantly related to performance goals. Although the relationship was weak ($r < .20$), the results indicate that students who believe they can perform generic tasks in their engineering courses may have the desire to demonstrate their competence to others. Given the assumption that students in engineering programs are academically gifted (e.g., being good in mathematics and/or science), successful performance of general engineering tasks demonstrates their competence to others. Students who believe in their capabilities to perform engineering tasks seem to also think that they should be able to master content in their courses and conduct basic research, at a minimum. The expectation of being smart enough to be in engineering may influence students to want to look smart to their peers and instructors.

Self-efficacy, intrinsic value, and utility value were positively correlated, consistent with results reported by Bong (2001a, 2001b). Researchers have asserted that interest plays a critical role in gendered occupational choices (Su, Rounds, & Armstrong, 2009). Engineering has been regarded a male-dominated field and a demanding career. Though this perceived cost about engineering prevails, the intrinsic value and utility value students assign to earning an engineering degree seems to propel them to work harder and to believe that they can perform engineering tasks required in their engineering coursework. Eccles (2005) suggested that students' choices to engage in activities, such as earning an engineering degree, are shaped by both ability beliefs and value beliefs. Furthermore, different patterns exist with respect to students' value beliefs about earning an engineering degree (Matusovich et al., 2010). Students may see the usefulness and or importance of an activity to their future plans that they muster the belief that they can do the task. Some students may believe they have the skills to successfully complete a task and find enjoyment in the process of completing the task.

The relationships between engineering self-efficacy and the outcome variables provided evidence of predictive validity. General engineering self-efficacy showed significant correlations with achievement outcomes. High general engineering self-efficacy scores were associated with higher grades (both in their engineering core courses and major courses). The correlations were in the expected directions. Tinkering skills self-efficacy was negatively related to engineering core GPA. This finding suggests that an increase in tinkering skills self-efficacy is accompanied by a decrease in engineering core GPA. Students who believe they can put things together and take things apart do not necessarily get high grades. This result was unexpected. One would assume that having confidence in one's tinkering skills would be beneficial to performance in engineering core courses, such as physics and chemistry that typically involve a laboratory class. Tinkering skills self-efficacy was operationalized in this study to reflect working with machines, building machines, manipulating devices, assembling things, and disassembling things. These are tasks that engineering students most likely perform in laboratory classes. Students in core engineering courses are being introduced to fundamental laws and principles in engineering (Nguyen, 1998). They are not only graded on their performance in laboratory classes but also on the mastery and understanding of course content. Though the magnitude of the relationship is small (r = -.18), this result warrants further investigation. For future research, researchers could identify courses where tinkering skills would matter and examine the relationship between tinkering skills self-efficacy and course grade. Current literature on tinkering includes use of science equipment and tools in constructing knowledge during science instruction (e.g., Baker, 2013; Jones et al., 2000). To date, literature pertaining to tinkering self-efficacy is limited and in the early stages (e.g., definition, development of measures).

In this study, engineering research skills self-efficacy involved performing tasks related to conducting experiments and communicating results of experiments, whereas engineering design self-efficacy dealt with designing solutions. These two types of engineering skills self-efficacy were not significantly correlated with any of the achievement outcomes. I hypothesized that research skills self-efficacy would be related to either of the engineering GPAs because research skills are typically needed throughout students' educational experience. I hypothesized that engineering design self-efficacy would be correlated with engineering major GPA because higher level classes (e.g., capstone) would require working on design projects. According to Schubert et al. (2012), the engineering design process "culminates in a capstone design experience in the senior year in which students apply the design process to a project specific to their major" (p. 187). The participants in this study included senior students; however, they were not the primary target sample population. Year level sampling could help explain the result regarding engineering design self-efficacy and engineering major GPA.

Group Differences in Engineering Self-Efficacy

The second goal of this study was to determine whether engineering students' self-efficacy scores differ with respect to students' gender, year level, or major. Having established that the engineering self-efficacy measures are psychometrically sound, I used students' scores on these measures to make the comparisons and test my hypotheses.

Gender. The self-efficacy scores for men and women in this sample were not significantly different. Findings in the literature on gender difference in engineering self-efficacy have been mixed. Concannon and Barrow (2009, 2012) did not find significant gender differences in engineering self-efficacy among engineering students. They attributed this finding to the quality of students in their sample. Students had similar abilities coming into college, high school grades, and college entrance scores. Others have found gender differences in engineering self-efficacy, however. For example, Jones et al. (2010) found that even when men and women had similar mean engineering GPAs at the end of their first year in college, men reported higher self-efficacy scores than women did. The authors speculated that men might have overestimated and women underestimated their abilities. Reisberg et al. (2010) also found that men had higher academic self-efficacy than women, who had higher career self-efficacy than men.

The inconsistency in findings could be due to the type of self-efficacy assessed and the various ways in which self-efficacy has been measured. Jones et al. (2010) assessed students' confidence in their ability to complete basic science (i.e., mathematics, physics, chemistry) requirements in their major with grades B or better. The other items in their self-efficacy scale asked about confidence in their abilities to excel in their engineering major in the future. On the other hand, Reisberg et al. (2010) used Lent et al.'s (1986) measure, Self-Efficacy for Academic Milestones and Self-Efficacy for Technical/Scientific fields. The finding in this dissertation study suggests that women believe in their general and skills-specific engineering capabilities just as much as men do. Women were equally prepared academically as the men (i.e., their average ACT math scores were not significantly different) and their engineering GPAs were comparable to their male counterparts'.

Year level. Studies examining self-efficacy across year levels have often focused on students' general engineering self-efficacy. Studies that examine engineering skills self-efficacy across year levels are limited. Thus, I investigated whether general and skills-specific engineering self-efficacy differed based on students' year level. No significant differences were found in the general engineering self-efficacy scores of lowerclassmen (freshmen and sophomores) and upperclassmen (juniors and seniors). Other researchers have reported similar findings (Concannon & Barrow, 2009; Marra & Bogue, 2006). Upperclassmen and lowerclassmen reported similar levels of engineering skills self-efficacy (i.e., research skills self-efficacy, tinkering skills self-efficacy, and engineering design self-efficacy). Contrary to the idea that upperclassmen would have higher engineering self-efficacy than lowerclassmen, the findings imply that the number of years in the engineering program does not necessarily translate to gains in engineering self-efficacy.

Major. Studies examining whether engineering self-efficacy differs as a function of students' major are scarce. Because each engineering discipline requires a specialized skill set that corresponds to the demands of a student's future profession, I hypothesized that students in different engineering majors would report different levels of tinkering skills self-efficacy and engineering design self-efficacy. In this dissertation study, tinkering skills self-efficacy differed by student major. Mechanical engineering majors reported higher tinkering skills self-efficacy scores than chemical and materials engineering majors. The focus of the engineering discipline may provide an explanation for the significant differences in tinkering self-efficacy as a function of major. Engineers are thought to have an inclination for tinkering with devices, machines, and tools to design products and improve processes. People in the field of engineering (students, faculty, and professionals) rank tinkering skills as an important characteristic of good engineers (Baker & Krause, 2007). However, the level of tinkering skills expected from engineering students likely varies depending on their major. Engineering curricula are designed to provide opportunities for students to engage in engineering tasks relevant to their major. If the development of tinkering skills is not an emphasis in a given program, students in that program may have low self-efficacy for such skills. Mechanical, civil, electrical, and computer engineering involve a focus on macro level and human-regulated systems, whereas chemical engineering focuses on micro level and largely inert materials (Shivy & Sullivan, 2005). Mechanical engineering majors engage in activities that incorporate use of tinkering skills, such as fixing equipment, fabricating parts, and basically dealing with gears and machinery. Civil engineering majors demonstrate their tinkering skills as they work with building materials, structural supports, and infrastructures. Electrical and computer engineering majors assemble and disassemble circuits, devices, and machines. On the other hand, chemical engineering majors may not have similar opportunities to work with machines and devices that are physically manipulated. Because mastery experience is the most influential source of self-efficacy (Bandura, 1997) and students who major in mechanical, civil, or electrical and computer engineering tend to have more successful task performances related to their tinkering skills, they are more likely to have higher tinkering self-efficacy than chemical engineering majors.

Predictive Utility of Engineering Self-Efficacy Scales

In this study, I sought to determine the unique contributions of engineering self-efficacy, achievement goals, and task value, to the prediction of achievement outcomes and intent to persist in engineering in a model controlling for gender, year level, major, and ACT mathematics score. I hypothesized that engineering self-efficacy and task value will predict achievement outcomes and intent to persist in engineering, and achievement goals will predict achievement and not intent to persist in engineering.

Predicting academic achievement. Engineering self-efficacy was a consistent predictor of academic achievement in engineering and added a significant proportion of the variance for each of the achievement outcomes (engineering core GPA and engineering major GPA). General engineering self-efficacy significantly predicted and contributed the most unique variance to both achievement outcomes. Previous research has demonstrated that self-efficacy is a significant predictor of engineering students' academic achievement (Hsieh et al., 2012; Lent et al., 1984, 1986) and that ACT mathematics scores predicted engineering GPA (e.g., Veenstra et al., 2008; Zhang et al, 2004). This dissertation study contributes to the literature by providing evidence that engineering self-efficacy adds to the prediction of students' engineering achievement even with ACT mathematics scores in the model. Ability, such as quantitative skills, has often been considered a strong determinant of academic success in engineering (Schaefers et al., 1998). The findings from this dissertation study suggest that, in addition to having requisite abilities, students' efficacy judgments of capabilities increase the likelihood of students achieving higher grades in engineering.

The unexpected finding in this study is the inverse relationship between tinkering skills self-efficacy and engineering core GPA. As discussed in an earlier section of this chapter, tinkering skills seem to be more relevant to students in certain majors. Students who work with macro-level systems have higher tinkering self-efficacy (e.g., mechanical engineering majors) than students who work with micro-level systems (e.g., chemical engineering majors). Tinkering skills self-efficacy may then be beneficial only to those who work with large scale systems as tinkering would be a skill required in their future profession. For mechanical engineering majors, having the belief to perform tasks that involve tinkering skills is relevant. Overall though, lack of belief in one's tinkering skills may not be detrimental to obtaining good grades in engineering courses. Future research should investigate the contributions of the different types of self-efficacy to achievement outcomes based on students' engineering major.

Task value and achievement goals did not contribute to the explained variance in students' engineering GPAs. Jones et al. (2010) reported that task value did not predict engineering GPA of first-year engineering students. Studies investigating the relationship of students' task value and engineering GPA are few, whereas studies examining engineering students' achievement goals and engineering GPA are scarce. Further research could shed more light into the relationship of these variables.

Predicting intent to persist in engineering. Engineering self-efficacy did not predict intent to persist in engineering professionally, a finding consistent with Jones et al. (2010). This finding indicates that students' belief in their capabilities to perform engineering tasks is not sufficient motivation for students to pursue engineering careers. Achievement goals did not add a significant proportion of the variance in intent to persist.

This suggests that engineering students' intention to persist in engineering is not influenced by reasons they pursue competence. Consistent with the findings of Jones et al. (2010), task value was the strongest predictor of students' intent to persist. In particular, intrinsic value contributed the most unique variance to the outcome. Task enjoyment and interest in engineering may be better predictors of the likelihood that students will pursue careers directly pertaining to engineering.

Values influence students' decisions to become engineers (Matusovich et al., 2010). In an interview, Eccles posited that opportunities to help others and to work in teams influence women's decisions to pursue engineering careers because these are what women value (Bembenutty, 2008). If students understand the significance of an engineering career to their personal goals, they are likely to persist in engineering. Thus, engineering educators could provide students with information about careers in engineering and emphasize the value of engineering to strengthen students' intent to persist.

Conclusion

I embarked on this study with the goal of developing engineering self-efficacy scales that capture the multifaceted nature of self-efficacy in the engineering domain. The general engineering self-efficacy scale and the engineering skills self-efficacy scale demonstrated acceptable reliability and validity. Certain types of engineering self-efficacy may be more relevant to students than others depending on their engineering discipline. Researchers and educators can use these scales to assess undergraduate engineering students' perceptions of their capabilities to perform tasks in their engineering programs and future roles as engineers. Measures of engineering self-efficacy could also help educators and researchers identify areas of task performance in which students feel less efficacious. Data gathered from engineering self-efficacy measures may guide researchers in the development of interventions to enhance students' judgments of their capabilities to function successfully in the domain of engineering.

Different sets of beliefs inform students of what they can do and what they can become. Some beliefs are general yet domain specific; other beliefs are task-specific. Level of specificity of measures and correspondence with the outcome of interest are important to achieve explanatory and predictive power. Engineering self-efficacy and task value predicted different outcomes. This finding implies that both motivation variables are needed to understand students' achievement and intent to persist in engineering.

Limitations and Future Directions

This scale validation study is exploratory in nature. Results must be interpreted with caution as findings have not been replicated. Further research should be conducted to validate the findings of this study. I recognize the limitations of this study and provide recommendations to improve future work related to the assessment of undergraduate students' engineering self-efficacy.

When selecting participants for a study, the goal is to select as large a sample as possible from the population to lessen sampling error (Creswell, 2012). A limited number of engineering students were invited to participate in the study based on the courses they were in. The recruitment process involved the cooperation of department chairs and instructors in the College of Engineering. Thus, the number of students recruited for the study were limited by the number of classes I was allowed to visit. In the future, having an advocate in the College of Engineering who is interested in examining academic achievement and student retention would be essential to gaining access to more engineering classes and possibly obtaining a larger sample size.

Data collection involved emailing students the link to the online survey. A common concern with online surveys is low response rates (Kwak & Radler, 2002; Nulty, 2008; Sheehan, 2001). Engineering students may have demanding class schedules and may be consequently inundated with school work such that completion of the survey was not a priority. To increase participation, I personally visited the engineering classes to talk about my study and informed students that I will be sending them an email invitation. Response rates are slightly better when the email invitation comes from a person compared to when the source was an office (Porter & Whitcomb, 2003). I also sent strategically timed email reminders to students who have not answered the survey at all and to those who have yet to complete the survey. Administration of a paper survey may help obtain better responses.

To measure accurately levels of engineering self-efficacy, accurate and honest responses are required from students. Self-reported data was used in this study. Such data are limited by the fact that they are individuals' own perspectives and cannot be verified (Barker, Pistrang, & Elliott, 2002). Another concern with self-reported data is social desirability. Individuals tend to present themselves in a favorable light, regardless of their true feelings about an issue or topic. Thus, social desirability has the potential to bias answers of respondents (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). As I recruited participants for the study, I informed them that all responses will be kept confidential, individual responses will not be singled out, and results will be reported in aggregate. I also reiterated that there are no right or wrong answers to the survey and encourage their candid responses. By doing this, I hoped to reduce the possibility of response bias.

Engineering grade point averages may not be the ideal measure of achievement in engineering but compared to cumulative GPAs, they do offer better correspondence to efficacy beliefs in engineering. This is a step towards addressing correspondence between self-efficacy measures and outcomes being measured. Scale developers may want to consider searching for outcomes more closely aligned with the type of self-efficacy they are measuring.

The study was a cross-sectional design that provides a snapshot of students' engineering self-efficacy, achievement, and intentions to persist in engineering. Participants in the study are at different stages in the program and may have different motivation profiles as a result of their experiences in particular engineering classes. Future work should include tracking a cohort of freshman engineering students and examining how their engineering self-efficacy, grades, and intentions to persist in engineering change as they navigate their way through engineering programs. Such a longitudinal study would be best suited most especially for research on persistence in engineering. The first two years in the engineering program have been regarded as the critical years in engineering. By conducting a longitudinal study, researchers can also compare changes in self-efficacy, achievement goals, and task values of students who stay or leave engineering after the first two years. Though it would be institution specific, the study could help identify turning point(s) in the engineering program. The results of a study such as this would guide educators and researchers in designing courses and revising curricula.

Much of the variance in the persistence outcome of this study needs to be explained. Researchers could investigate the unique contributions of other motivation variables. For example, researchers have investigated grit and implicit theories of ability to explain persistence in tasks. Grit, defined as perseverance and passion for long-term goals, predicts success over and beyond mental ability and conscientiousness (Duckworth, Peterson, Matthews, & Kelly, 2007). On the other hand, the belief one holds about the nature of abilities (i.e., implicit beliefs) can lead to loving challenges, believing in effort, and remaining resilient when faced with setbacks (Dweck, 2006). Dweck (2006) also referred to these beliefs as mindsets about the origins of students' own ability. Two mindset tendencies exist: a fixed mindset (belief that ability is innate and there is nothing you can do about it) and a growth mindset (belief that ability is acquired, can be changed, and developed). Grit and implicit theories of abilities are believed to change over time. Adding them to the list of variables in a future longitudinal study mentioned above may help explain variance in persistence in engineering.

Copyright © Natasha Johanna A. Mamaril 2014

Appendix A: IRB Approval

[redacted]

[redacted]

Continuation Expedited Review

Approval Ends
August 13, 2014

IRB Number
12-0628-P4S

TO: Natasha Mamaril, MS
Education Psych & Counseling
[redacted]

FROM: Chairperson/Vice Chairperson
Non-medical Institutional Review Board (IRB)

SUBJECT: Approval of Protocol Number 12-0628-P4S

DATE: August 19, 2013

On August 14, 2013, the Non-medical Institutional Review Board approved your protocol entitled:

Development and Validation of an Engineering Self-Efficacy Scale for College Students

Approval is effective from August 14, 2013 until August 13, 2014 and extends to any consent/assent form, cover letter, and/or phone script. If applicable, attached is the IRB approved consent/assent document(s) to be used when enrolling subjects. [Note, subjects can only be enrolled using consent/assent forms which have a valid "IRB Approval" stamp unless special waiver has been obtained from the IRB.] Prior to the end of this period, you will be sent a Continuation Review Report Form which must be completed and returned to the Office of Research Integrity so that the protocol can be reviewed and approved for the next period.

In implementing the research activities, you are responsible for complying with IRB decisions, conditions and requirements. The research procedures should be implemented as approved in the IRB protocol. It is the principal investigator's responsibility to ensure any changes planned for the research are submitted for review and approval by the IRB prior to implementation. Protocol changes made without prior IRB approval to eliminate apparent hazards to the subject(s) should be reported in writing immediately to the IRB. Furthermore, discontinuing a study or completion of a study is considered a change in the protocol's status and therefore the IRB should be promptly notified in writing.

For information describing investigator responsibilities after obtaining IRB approval, download and read the document "PI Guidance to Responsibilities, Qualifications, Records and Documentation of Human Subjects Research" from the Office of Research Integrity's Guidance and Policy Documents web page [redacted] Additional information regarding IRB review, federal regulations, and institutional policies may be found through ORI's web site [redacted]. If you have questions, need additional information, or would like a paper copy of the above mentioned document, contact the Office of Research Integrity at (859) 257-9428.

Chairperson/Vice Chairperson

1

An Equal Opportunity University

Appendix B: College of Engineering Curriculum Matrix

	Major							
Course	CHE	CE	CompE	BAE	EE	MSE	ME	MinE
Introduction to Biosystems Engineering				F1				
Energy in Biological Systems				F2				
Economic Analysis for Biosystems				F2				
Statistical Inferences in Biosystems		So1		So2				
DC Circuits and Microelectronics				J2				
Senior Seminar				Se1				
Biosystems and Agricultural Engineering Design I				Se1				
Biosystems and Agricultural Engineering Design II				Se2				
Principles of Biology I				So1				
Principles of Biology II				J1				
Computer Graphics and Communication		F2		F2				
Introduction to Civil Engineering		F1						
Introduction to Construction Engineering		J1						
Civil Engineering Communications		J1						
Transportation Engineering		J2						
Introduction to Fluid Mechanics		J1		J1				
Introduction to Environmental Engineering		J2						
Civil Engineering Materials I		J1						
Structural Analysis		J2						
Seminar		Se2						
Civil Engineering Systems Design		Se2						
Water Resources Engineering		Se1						
Soil Mechanics		Se1						
Structures Elective		Se1						
CE Technical Design		Se1						
General College Chemistry I	F1	F2	F1	F1	F2	F1	F1	F1
General College Chemistry II	F2	So1		F2		F2	F2	F2

Appendix B (continued)

	Major							
	CHE	CE	CompE	BAE	EE	MSE	ME	MinE
Laboratory to Accompany General Chemistry I	F1					F1	F1	
Laboratory to Accompany General Chemistry II	F2					F2		
Organic Chemistry I	So1							
Organic Chemistry Laboratory I	So1							
Organic Chemistry II	So2							
Survey of Organic Chemistry						So1		
Physical Chemistry for Engineers	J1							
The Engineering Profession	J2							
Introduction to Chemical Engineering	F1							
Process Principles	So1					J1		
Computational Tools in Chemical Engineering	So2							
Engineering Thermodynamics	So2							
Fluid Mechanics	J1							
Separation Processes	J1							
Process Modeling in Chemical Engineering	J2							
Heat and Mass Transfer	J2							
Chemical Engineering Laboratory I	J2							
Chemical Engineering Laboratory II	Se1							
Chemical Engineering Process Design I	Se1							
Chemical Engineering Process Design II	Se2							
Process Control	Se2							
Professionalism, Ethics and Safety	Se1							
Chemical Reactor Design	Se1							
The Computer Science Profession			F1					
Introduction to Computer Programming			F1		F1			
Introduction to Program Design			So1		So2			
Introduction to Software Engineering			So2					

Appendix B (continued)

	Major							
	CHE	CE	CompE	BAE	EE	MSE	ME	MinE
First Course in Computer Science for Engineers		So2		So1		F2	So1	F1
Algorithm Design and Analysis			J1					
Discrete Mathematics			So2					
Algorithm Design and Analysis			J1					
Compilers for Algorithmic Languages			Se1					
Introduction to Operating Systems			J2					
Senior Design Project			Se2					
Creativity and Design in Electrical and Computer Engineering			F1		F1			
Circuits I			So1		So1			
Circuits II			J1		So2			
Electrical Engineering Laboratory I			J1		So2			
Design of Logic Circuits			F2		F2			
Logical Design Laboratory			So1					
Electrical Circuits and Electronics				J1		Se1	J1	J1
Introduction to Semiconductor Devices					So2			
Microcomputer Organization					J1			
Introduction to Embedded Systems			J1					
Electromechanics					J1			
Signals and Systems			J2		J1			
Introduction to Electronics			J2					
Introduction to Engineering Electromagnetics					J2			
Advanced Computer Architecture			J2					
Electrical Engineering Capstone Design I					Se1			
EE 491 Electrical Engineering Capstone Design II					Se2			
Microcomputer Organization			So2					
Statics		So1		So2		So2	So2	So1
Mechanics of Deformable Solids		So2		J1		J1	J1	So2

Appendix B (continued)

	Major							
	CHE	CE	CompE	BAE	EE	MSE	ME	MinE
Dynamics				J1/J2			J1	J2
Principles of Physical Geology		J1						So1
Fundamentals of Geology I								J1
Calculus I	F1	F1	F1	F1	F1	F1		F1
Calculus II	F2	F2	F2	F2	F2	F2	F2	F2
Calculus III	So1	So1	So1	So1	So1	So1	So1	So1
Calculus IV	So2	So2	So2	So2	So2	So2	So2	So2
Introductory Probability					J1			
Introduction to Mechanical Engineering							F1	
Manufacturing Engineering							F2	
Computer Aided Engineering Graphics							So1	
Engineering Thermodynamics I				So2			So2	So2
Engineering Experimentation I							J2	
Engineering Experimentation II							Se1	
Engineering Thermodynamics II							J1	
Elements of Heat Transfer				J2			J2	
Fluid Mechanics							J1	J1
Introduction to Mechanical Systems				Se2			J2	
Mechanical Design							J2	
ME Capstone Design I							Se1	
ME Capstone Design II							Se2	
Design of Control Systems							Se1	
Mechanical Design with Finite Element Methods							Se1	
Introduction to Mining Engineering								F1
Mine Graphics								F2
Mine Surveying								J1
Mining Methods								F2
Mineral Reserve Modeling								So2
Minerals Processing								J1
Minerals Processing Laboratory								J1
Deformable Solids Laboratory								So2

Appendix B (continued)

	Major							
	CHE	CE	CompE	BAE	EE	MSE	ME	MinE
Mine Safety and Health Management and Processes								So2
Explosives and Blasting								So1
Mine Plant Machinery								Se1
Introduction to Mine Systems Analysis								J1
Mine Ventilation								Se1
Professional Development of Mining Engineers								J2
Mine Systems Engineering and Economics								J2
Surface Mine Design and Environmental Issues								J2
Rock Mechanics								Se1
Mine Design Project I								Se1
Mine Design Project II								Se2
Materials Engineering						F1		
Materials Science	F2							
Materials Science Laboratory						So1		
Materials Science II						So2		
Material Thermodynamics						So2		
Metal and Alloys						J1		
Electronic Materials and Processing						J2		
Ceramic Engineering and Processing						J2		
Polymeric Materials						J1		
Materials Laboratory I						J2		
Materials Laboratory II						Se1		
Material Failure Analysis						Se1		
Materials Design						Se2		
Mechanical Properties of Materials						J2		
Metals Processing						Se2		
Materials Characterization Techniques						Se1		
General University Physics	So1	F1	F2	So1	F2	So1	So1	F2
General University Physics	So2	So2	So1	So2	So1	So2	So2	So1
General University Physics Laboratory	So1	F1	F2	So1	F2	So1	So1	F2

Appendix B (continued)

	Major							
	CHE	CE	CompE	BAE	EE	MSE	ME	MinE
General University Physics Laboratory		So2	So1	So2	So1		So2	So1
Principles of Modern Physics						J2		
Introduction to Engineering Statistics			J1					

Legend:

F1 – 1st semester freshmen
F2 – 2nd semester freshmen
So1 – 1st semester sophomore
So2 – 2nd semester sophomore
J1 – 1st semester junior
J2 – 2nd semester junior
Se1 – 1st semester senior
Se2 – 2nd semester senior

Appendix C: Email Invitation to Participate in the Study

Subject: Invitation to Participate in Survey for Engineering Students

Dear (Student's First Name),

You are invited to participate in a study about attitudes and beliefs about engineering. This study is being conducted by Natasha Mamaril, a graduate student of the University of Kentucky department of Educational, School, and Counseling Psychology, to examine the psychological factors related to engineering students' academic performance and persistence in engineering programs.

You are being invited to take part in this research because you are an engineering student at the [redacted] College of Engineering and at least 18 years of age.

Your participation in this survey is completely voluntary. Your responses will be kept confidential. The results of the survey will be reported in such a way that individual responses cannot be identified. The survey takes approximately 15 minutes to complete. If you decide to participate, please complete the survey by (Day of the Week), (Month Day), (Year).

Below is your password to access the survey. Please enter this password when prompted: (electronically generated password shows up here)

Click this link to access the survey:
(insert survey link here)

If you experience technical difficulties, please email tashmamaril@uky.edu.

Thank you,

Natasha Mamaril
Member, P20 Motivation and Learning Lab
College of Education
University of Kentucky

Appendix D: Achievement Goal Orientation Scale

Mastery Goals (Adapted from Harackiewicz et al., 2000)

1. I want to learn as much as possible in this engineering class.
2. In an engineering class, I prefer course material that really challenges me so I can learn new things.
3. The most important thing for me in an engineering class is trying to understand the content as thoroughly as possible.
4. Understanding engineering is important to me.
5. I like it best when something I learn makes me want to find out more.
6. In an engineering class, I prefer course material that arouses my curiosity, even if it is difficult to learn.

Performance Approach Goals (Adapted from Harackiewicz et al., 2000)

7. It is important for me to do better than other students.
8. My goal in this engineering class is to get a better grade than most of the other students.
9. It is important for me to do well compared to other engineering students in this class/program.
10. I want to do well in this class to show my ability to my family, friends, advisors, or others.
11. Getting a good grade in this class is the most important thing for me right now.
12. It is important for me to establish a good overall grade-point average, so my main concern in this class is getting a good grade.

Performance Avoidance Goals (PALS items by Midgley et al., 2000)

13. It's important to me that I don't look stupid in my engineering class.
14. One of my goals in my engineering class is to avoid looking like I have trouble doing the work.
15. It's important to me that my instructor doesn't think that I know less than other students in my engineering class.
16. One of my goals is to keep other engineering students from thinking I'm not smart in class.

Appendix E: Task Value Scale

Intrinsic Value (Items taken from Li et al., 2008)

1. I would like to design new products to make people's lives more convenient.
2. I like to know how things work. (new item)
3. Solving a challenging engineering problem is rewarding.
4. I like engineering design projects.
5. Science is one of my favorite subjects.
6. I would like to play a role in advanced technology development in the future.
7. I find subjects requiring quantitative analysis interesting.
8. Engineering is exciting.
9. I enjoy reading about new technological innovations.
10. I would like to have a career involving innovative engineering products design.
11. I enjoy watching TV programs on technology related topics.
12. I would like to be an engineer.

Cost Value (Items taken from Li et al., 2008)

13. Engineering is a tough program.
14. Engineering is a tough career.
15. To earn an engineering degree takes much effort.

Attainment Value (Item taken from Jones et al., 2010)

16. The amount of effort it will take to do well in engineering courses is worthwhile to me.

Utility Value (New Items)

17. Engineers are well paid.
18. An engineering degree leads to a profitable career.
19. Engineering degrees are good for getting industry jobs.
20. Engineering degrees offer a wide range of employment options.

Appendix F: Persistence Scale

Academic Persistence (Items taken from Eris et al., 2010)

1. I intend to enroll in engineering courses next semester.
2. I intend to complete all requirements for my engineering degree program.

Professional Persistence (Items taken from Eris et al., 2010)

3. I intend to practice engineering for at least 3 years after I graduate.
4. I intend to conduct research in engineering for at least 3 years after I graduate.

Appendix G: Descriptive Statistics for Study Variables

Variables	*M*	*SD*	Skewness	Kurtosis
Self-Efficacy				
General Engineering Self- Efficacy	4.95	0.75	-0.40	-0.62
Research Skills Self-Efficacy	4.88	0.74	-0.35	-0.16
Tinkering Skills Self-Efficacy	4.78	0.92	-0.62	0.08
Engineering Design Skills Self-Efficacy	4.77	0.90	-0.49	-0.03
Achievement Goals				
Mastery	5.12	0.61	-0.78	1.80
Performance Approach	4.49	1.05	-0.87	0.87
Performance Avoidance	3.73	1.28	-0.25	-0.62
Task Value				
Intrinsic Value	5.07	0.68	-0.79	1.18
Cost	5.31	0.71	-1.55	-5.40
Utility Value	5.29	0.56	-0.35	-0.44
Achievement				
ACT Mathematics Score	29.06	4.25	-0.60	0.13
Engineering Core GPA	3.11	0.69	-0.41	-0.62
Engineering Major GPA	3.30	0.59	-0.72	-0.09
Intent to Persist in Engineering				
Intent to Persist Academically	5.57	0.94	-2.85	9.13
Intent to Persist Professionally	4.24	1.07	-1.05	1.27

Note. GPA = Grade Point Average
N = 224

References

Accreditation Board for Engineering and Technology. (2013). Criteria for accrediting engineering programs. Retrieved from http://www.abet.org/DisplayTemplates/DocsHandbook.aspx?id=3149

Assessing Women and Men in Engineering. (n.d.). STEM Assessment Tools. Retrieved from https://www.engr.psu.edu/awe/secured/director/diversity/efficacy.aspx

Baker, D. (2013). What works: Using curriculum and pedagogy to increase girls' interest and participation in science. *Theory Into Practice, 52,* 14-20. doi:10.1080/07351690.2013.743760

Baker, D., & Krause, S. (2007). Do tinkering and technical activities connect engineering education standards with the engineering profession in today's world? *American Society for Engineering Education Annual Conference and Exposition*. Honolulu, Hawaii.

Baker, D., Krause, S., & Purzer, S. (2008). Developing an instument to measure tinkering and technical self-efficacy in engineeirng. *American Society for Engineering Education Annual Conference and Exposition.* Pittsburgh, Pennsylvania.

Baker, D., Krause, S., Yasar, S., Roberts, C., & Robinson-Kurpius, S. (2007). An intervention to address gender issues in a course on design , engineering , and technology for science educators. *Journal of Engineering Education*, *96*, 213–226. Retrieved from http://jee.org/2007/july/4.pdf

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: Freeman.

Bandura, A. (2006). Guide for constructing self-efficacy scales. In F. Pajares & T. Urdan (Eds.), *Self-efficacy beliefs of adolescents* (pp. 307-337). Greenwich, CT: Information Age Publishing.

Barker, C., Pistrang, N., & Elliott, R. (2002). *Research methods in clinical psychology: An introduction for students and practitioners (2nd Ed.).* West Sussex, England: Wiley and Sons, Ltd. doi:10.1002/0470013435

Bembenutty, H. (2008). The last word: The scholar whose expectancy-value theory transformed the understanding of adolescence, gender differences, and achievement: An interview with Jacquelynne S. Eccles. *Journal of Advanced Academics, 19,* 531-550. doi:10.4219/jaa-2008-811

Bernold, L. E., Spurlin, J. E., & Anson, C. M. (2007). Understanding our students : A longitudinal-study of success and failure in engineering. *Journal of Engineering Education*, *96*(3), 263–274. Retrieved from http://www.jee.org/2007/july/2.pdf

Besterfield-Sacre, M. B., Atman, C. J., & Shuman, L. J. (1997). Characteristics of freshman engineering students : Models for determining student attrition in engineering. *Journal of Engineering Education*, *86*(2), 139–149. Retrieved from http://www.jee.org/1997/april/54.pdf

Betz, N. E., & Fitzgerald, L. F. (1987). *The career psychology of women.* Orlando, FL: Academic Press.

Betz, N. E., & Hackett, G. (1981). The relationship of career-related self-efficacy expectations to perceived career options in college women and men. *Journal of Counseling Psychology, 28*, 399-410.

Betz, N. E., & Hackett, G. (1983). The relationship of mathematics self-efficacy expectations to the selection of science-based college majors. *Journal of Vocational Behavior, 23*, 329-345.

Bong, M. (2001a). Role of self-efficacy and task-value in predicting college students' course performance and future enrollment intentions. *Contemporary Educational Psychology*, *26*(4), 553–570. doi:10.1006/ceps.2000.1048

Bong, M. (2001b). Between- and within-domian relations of academic motivation among middle and high school students: Self-efficacy, task value, and achievment goals. *Journal of Educational Pychology, 93,* 23-34. doi:10.I037//0022-0663.93.1.23

Bong, M. (2006). Asking the right question: How confident are you that you could successfully perform these tasks? In F. Pajares & T. Urdan (Eds.), *Self-efficacy beliefs of adolescents* (pp. 287-305). Greenwich, CT: Information Age Publishing.

Bong, M., & Hocevar, D. (2002). Applied measurement in education measuring self-efficacy : Multitrait-multimethod comparison of scaling procedures. *Applied Measurement in Education*, *15*, 143–171. doi:10.1207/S15324818AME1502_02

Brainard, S., & Carlin, L. (1998). A six-year longitudinal study of undergraduate women in engineering and science. *Journal of Engineering Education, 87*, 369-375.

Burn, H., & Holloway, J. (2006). Why should I care? Student motivation in an introductory programming course. *Proceedings of the American Society for Engineering Education 2006 Annual Conference and Exhibition,* Chicago, Illinois.

Carberry, A. R., Lee, H. S., & Ohland, M. W. (2010). Measuring engineering design self-efficacy. *Journal of Engineering Education*, *99*, 71–80. Retrieved from http://www.jee.org/2010/january/8.pdf

Cerny, C. A., & Kaiser, H. F. (1977). A study of a measure of sampling adequacy for factor-analytic correlation matrices. *Multivariate Behavioral Research, 12,* 43-47.

Clement, S. (1987). The self-efficacy expectations and occupational preferences of females and males. *Journal of Occupational Psychology, 60,* 257-265.

Cohen, J. (1988). *Statistical power analyses for the behavioral sciences* (2nd ed.). New Jersey: Lawrence Erlbaum Associates, Inc.

Cole, J. S., Bergin, D. A., & Whittaker, T. A. (2008). Predicting student achievement for low stakes tests with effort and task value. *Contemporary Educational Psychology*, *22*, 609-624.

Concannon, J. P., & Barrow, L. H. (2008). A cross-sectional study of freshmen engineering majors' self-efficacy. *Proceedings of the American Society for Engineering Education 2008 Annual Conference and Exhibition,* Pittsburgh, Pennsylvania.

Concannon, J. P., & Barrow, L. H. (2009). A cross-sectional study of engineering students' self-efficacy by gender, ethnicity, year, and transfer status. *Journal of Science Education and Technology*, *18*(2), 163–172. doi:10.1007/s10956-008-9141-3

Concannon, J. P., & Barrow, L. H. (2010). Men's and women's intentions to persist in undergraduate engineering degree programs. *Journal of Science Education and Technology*, *19*(2), 133–145. doi:10.1007/s10956-009-9187-x

Concannon, J. P., & Barrow, L. H. (2012). A reanalysis of engineering majors' self-efficacy beliefs. *Journal of Science Education and Technology*, *21,* 1–12. doi:10.1007/s10956-011-9362-8

Courville, T., & Thompson, B. (2001). Use of structure coefficients in published multiple regression articles: ß is not enough. *Educational and Psychological Measurement, 61*, 229-248. doi:10.1177/0013164401612006

Creswell, J. W. (2012). *Educational research* (4th ed.). Boston: Pearson Education.

DeVellis, R. F. (1991). *Scale development: Theory and applications.* Newbury Park, California: Sage Publications.

Dorans, N. J. (1999). *Correspondences between ACT and SAT I Scores.* (College Board Report No. 99-1; ETS RR No. 99-2). New York: College Entrance Examination Board and Educational Testing Service.

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology, 92,* 1087-1101. doi:10.1037/0022-3514.92.6.1087

Dunlap, J. C. (2005). Problem-based learning and self-efficacy: How a capstone course prepares students for a profession. *Educational Technology Research and Development*, *53*, 65–85.

Dunsmore, K., Turns, J., & Yellin, J. M. (2011). Looking toward the real world: Student conceptions of engineering. *Journal of Engineering Education, 100,* 329-348. doi:10.1002/j.2168-9830.2011.tb00016.x

Durik, A. M., Lovejoy, C. M., & Johnson, S. J. (2009). A longitudinal study of achievement goals for college in general: Predicting cumulative GPA and diversity in course selection. *Contemporary Educational Psychology*, *34*(2), 113–119. doi:10.1016/j.cedpsych.2008.11.002

Dweck, C. S. (2006). *Mindset: The new psychology of success.* New York: Random House.

Eccles, J. S. (2005). Subjective task value and the Eccles et al. model of achievement-related choices. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105-121), New York: Guilford.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21,* 215-225. doi:10.1177/0146167295213003

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*, 109–132. doi:10.1146/annurev.psych.53.100901.135153

Elliot, A. J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist, 34,* 169-189.

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72,* 218-232.

Eris, O., Chachra, D., Chen, H. L., Sheppard, S., Ludlow, L., Rosca, C., … George, T. (2010). Outcomes of a longitudinal administration of the persistence in engineering survey. *Journal of Engineering Education*, *99*, 371–395. Retrieved from http://www.jee.org/2010/october/8.pdf

Fantz, T. D., Siller, T. J., & DeMiranda, M. A. (2011). Pre-collegiate factors influencing the self-efficacy of engineering students. *Journal of Engineering Education*, *100*, 604–623. Retrieved from http://www.mycahs.colostate.edu/Michael.DeMiranda/Fantz_Siller_de_Miranda_JEE_2011.pdf

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). London: Sage Publications.

French, B., Immekus, J., & Oakes, W. (2005). An examination of indicators of engineering students' success and persistence. *Journal of Engineering Education*, *94*, 419–425. doi:10.1002/j.2168-9830.2005.tb00869.x

Gorsuch, R. L. (1983). *Factor analysis* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Hackett, G., Betz, N., Casas, M., & Rocha-Singh, I. A. (1992). Gender, ethnicity, and social cognitive factors predicting the academic achievement of students in engineering. *Journal of Counseling Psychology*, *39*, 527–538. doi:10.1037//0022-0167.39.4.527

Harackiewicz, J. M., Barron, K. E., & Elliot, A. J. (1998). Rethinking achievement goals: When are they adaptive for college students and why? *Educational Psychologist*, *33*, 1–21. doi:10.1207/s15326985ep3301_1

Harackiewicz, J. M., Barron, K. E., & Elliot, A. J. (2000). Short-term and long-term consequences of achievement goals: Predicting interest and performance over time. *Journal of Educational Psychology*, *92*, 316–330. doi:10.1037/0022-0663.92.2.316

Heyman, G. D., Martyna, B., & Bhatia, S. (2002). Gender and achievement-related beliefs among engineering students. *Journal of Women and Minorities in Science and Engineering*, *8*, 41–52. Retrieved from http://lmrt.mit.edu/publications/2002/Heyman2002_JWomMinSciEng.pdf

Hsieh, P., Sullivan, J. R., & Guerra, N. S. (2007). A closer look at college students: Self-efficacy and goal orientation. *Journal of Advanced Academics2*, *18*(3), 454–476.

Hsieh, P., Sullivan, J. R., Sass, D. a., & Guerra, N. S. (2012). Undergraduate engineering students' beliefs, coping strategies, and academic performance: An evaluation of theoretical models. *The Journal of Experimental Education*, *80*, 196–218. doi:10.1080/00220973.2011.596853

Hutchison, M., Follman, D., & Bodner, G. (2007). The changing tides : How engineering environments play a role in self-efficacy belief modification. *American Society for Engineering Education Annual Conference and Exposition*. Honolulu, Hawaii.

Hutchison, M., Follman, D. K., Sumpter, M., & Bodner, G. M. (2006). Factors influencing the self-efficacy beliefs of first-year engineering students. *Journal of Engineering Education*, *95*, 39–47. doi:10.1002/j.2168-9830.2006.tb00876.x

Hutchison-Green, M. A., Follman, D. K., & Bodner, G. M. (2008). Providing a voice : Qualitative investigation of the impact of a first-year engineering experience on students' efficacy beliefs. *Journal of Engineering Education*, *97*(2), 177–190. doi:10.1002/j.2168-9830.2008.tb00966.x

Jackson, L. A., Gardner, P. D., & Sullivan, L. A. (1993). Engineering persistence: Past, present, and future factors and gender differences. *Higher Education, 26,* 227-246. doi:10.1007/BF01406954

Jagacinski, C. M., LeBold, W.K., & Linden, K.W. (1987). The relative career advancement of men and women engineers in the United States. *Work and Stress, 1*, 1-13. doi:10.1080/02678378708258507

Jones, B. D., Paretti, M. C., Hein, S. F., & Knott, T. W. (2010). An analysis of motivation constructs with first-year engineering students: Relationships among expectancies, values, achievement, and career plans. *Journal of Engineering Education*, *99*, 319–336. doi:10.1002/j.2168-9830.2010.tb01066.x

Jones, M. G., Brader-Araje, L., Carboni, L. W., Carter, G., Rua, M. J., Banilower, E., & Hatch, H. (2000). Tool time: Gender and students' use of tools, control, and authority. *Journal of Research in Science Teaching, 37,* 760-783. doi:10.1002/1098-2736(200010)37:8<760::AID-TEA2>3.0.CO;2-V

Kaiser, H. F. (1970). A second generation little jiffy. *Psychometrika, 35,* 401-415. doi:10.1007/BF02291817

Kinsey, B. L., Towle, E., O'Brien, E. J., & Bauer, C. F. (2008). Analysis of self-efficacy and ability related to spatial tasks and the effect on retention for students in engineering. *International Journal of Engineering Education*, *24*(3), 488–494. Retrieved from http://www.ingentaconnect.com/content/intjee/ijee/2008/00000024/00000003/art00005

Kline, R. B. (1998). *Principals and practice of structural equation modeling*. New York: Guilford.

Kraha, A., Turner, H., Nimon, K., Zientek, L. R., & Henson, R. K. (2012). Tools to support interpreting multiple regression in the face of multicollinearity. *Frontiers in Psychology, 3,* 1-16. doi:10.3389/fpsyg.2012.00044

Kwak, N., & Radler, B. (2002). A comparison between mail and web surveys: Response pattern, respondent profile, and data quality. *Journal of Official Statistics, 18,* 257-273. Retrieved from http://www.barold.com/www/jos%20article.pdf

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior, 45,* 79-122. doi:10.1006/jvbe.1994.1027

Lent, Robert W., Brown, S. D., & Larkin, K. C. (1984). Relation of self-efficacy expectations to academic achievement and persistence. *Journal of Counseling Psychology*, *31*, 356–362. doi:10.1037//0022-0167.31.3.356

Lent, Robert W., Brown, S. D., & Larkin, K. C. (1986). Self-efficacy in the prediction of academic performance and perceived career options. *Journal of Counseling Psychology*, *33*, 265–269. doi:10.1037//0022-0167.33.3.265

Lent, R. W., Brown, S. D., Sheu, H. B., Schmidt, J., Brenner, B. R., Gloster, C. S., …Lyons, H. (2005). Social cognitive predictors of academic interests and goals in engineering: Utility for women and students at historically Black universities. *Journal of Counseling Psychology, 52,* 84-92. doi:10.1037/0022-0167.52.1.84

Lent, Robert W., Sheu, H.-B., Gloster, C. S., & Wilkins, G. (2010). Longitudinal test of the social cognitive model of choice in engineering students at historically Black universities. *Journal of Vocational Behavior*, *76*, 387–394. doi:10.1016/j.jvb.2009.09.002

Lent, R. W., Sheu, H.-B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior*, *73*, 328–335. doi:10.1016/j.jvb.2008.07.005

Lent, R. W., Singley, D., Sheu, H.-B., Schmidt, J. A., & Schmidt, L. C. (2007). Relation of social-cognitive factors to academic satisfaction in engineering students. *Journal of Career Assessment*, *15*, 87–97. doi:10.1177/1069072706294518

Levin, J., & Wyckoff, J. (1990). *Identification of student characteristices that predict persistence and success in an engineering college at the end of the sophomore year: Informing the practice of academic advising* (DUF-1990.1). Retrieved from http://files.eric.ed.gov/fulltext/ED319355.pdf

Li, Q., McCoach, D. B., Swaminathan, H., & Tang, J. (2008). Development of an instrument to measure perspectives of engineering education. *Journal of Engineering Education*, *97*, 47–56. doi:10.1002/j.2168-9830.2008.tb00953.x

Marra, R. M., & Bogue, B. (2006). Women engineering students' self-efficacy: A longitudinal multi-institution study. *Proceedings of the 2006 Women in Engineering Programs and Advocates Network.* Pittsburgh, Pennsylvania. Retrieved from http://ojs.libraries.psu.edu/index.php/wepan/article/viewFile/58479/58167

Marra, R. M., Rodgers, K. A., Shen, D., & Bogue, B. (2009). Women engineering students and self-efficacy : A multi-year , multi-institution study of women engineering student self-efficacy. *Journal of Engineering Education*, *98*, 27–38. doi:10.1002/j.2168-9830.2009.tb01003.x

Martin, J. H., Hands, K. B., Lancaster, S. M., Trytten, D. A., & Murphy, T. J. (2008). Hard but not too hard: Challenging courses and engineering students. *College Teaching, 56,* 107-113. doi:10.3200/CTCH.56.2.107-113

Matusovich, H. M., Streveler, R. A., & Miller, R. L. (2010). Why do students choose engineering? A qualitative, longitudinal investigation of students' motivational values. *Journal of Engineering Education*, *99*, 289–303. doi:10.1002/j.2168-9830.2010.tb01064.x

Meece, J. L., Wigfield, A., & Eccles, J. S. (1990). Predictors of math anxiety and its influence on young adolescents' course enrollment intentions and performance in mathematics. *Journal of Educational Psychology, 82,* 60-70. doi:10.1037/0022-0663.82.1.60

Middleton, M. J., & Midgley, C. (1997). Avoiding the demonstration of lack of ability: An under-explored aspect of goal theory. *Journal of Educational Psychology, 89*, 710-718. doi:10.1037/0022-0663.89.4.710

Midgley, C., Kaplan, A., Middleton, M., Maehr, M. L., Urdan, T., Anderman, L. H., … Roeser, R. (1998). The development and validation of scales assessing students' achievement goal orientations. *Contemporary Educational Psychology, 23*, 113-131. doi:10.1006/ceps.1998.0965

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., …Urdan, T. (2000). *Manual for the patterns of adaptive learning scales.* Ann Arbor, MI: University of Michigan.

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology*, *38*, 30–38. doi:10.1037//0022-0167.38.1.30

Nathans, L. L., Oswald, F. L., Nimon, K. (2012). Interpreting multiple linear regression: A guidebook of variable importance. *Practical Assessment, Research and Evaluation, 17,* 1-16. Retrieved from http://pareonline.net/pdf/v17n9.pdf

National Science Board. (2012). *Science and Engineering Indicators 2012.* Arlington, VA: National Science Foundation (NSB 12-01).

Nguyen, D. Q. (1998). The essential skills and attributes of an engineer: A comparative study of academics , industry personnel and engineering students. *Global Journal of Engineering Education*, *2*(1), 65–76. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.124.1502&rep=rep1&type=pdf

Nulty, D. D. (2008). The adequacy of response rates to online and paper surveys: what can be done? *Assessment and Evaluation in Higher Assessment, 33,* 301-314. doi:10.1080/02602930701293231

Osborne, J. W., Costello, A. B., & Kellow, J. T. (2008). Best practices in exploratory factor analysis. In J. W. Osborne (Ed.), *Best practices in quantitative methods* (pp. 205-213). Thousand Oaks, CA: Sage Publishing.

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research*, *66*(4), 543. doi:10.2307/1170653

Pallant, J. (2010). *SPSS survival manual: A step by step guide to data analysis using SPSS* (4th ed.). Maidenhead: McGraw Hill.

Panchal, J. H., Adesope, O., & Malak, R. (2012). Designing undergraduate design experiences: A framework based on the expectancy-value theory. *International Journal of Engineering Education, 28,* 871-879. Retrieved from http://www.ijee.ie/latestissues/Vol28-4/15_ijee2610ns.pdf

Pearson, R. W. (2010). *Statistical persuasion.* Thousand Oaks, CA: Sage Publications.

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research.* Thousand Oaks, California: Sage Publications.

Pintrich, P. R. (2000). An achievement goal theory perspective on issues in motivation terminology, theory, and research. *Contemporary Educational Psychology*, *25*, 92–104. doi:10.1006/ceps.1999.1017

Pintrich, P. R., & Schunk, D. H. (1996). *Motivation in education: Theory, research, and applications*. Englewood Cliffs, NJ: Merrill/Prentice Hall.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. Ann Arbor: University of Michigan, National Center for Research to Improve Postsecondary Teaching and Learning.

Pintrich, P. R., & Zusho, A. (2002). The development of academic self-regulation: the role of cognitive and motivational factors. In A. Wigfield, & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 249–284). San Diego: Academic Press.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88,* 879-903. doi:10.1037/0021-9010.88.5.879

Ponton, M. K. (2002). Motivating students by building self-efficacy. *Journal of Professional Issues in Engineering Education and Practice, 128,* 54-57. doi:10.1061/(ASCE)1052-3928(2002)128:2(54)

Ponton, M. K., Edmister, J. H., Ukeiley, L. S., & Seiner, J. M. (2001). Understanding the role of self-efficacy in engineering education. *Journal of Engineering Education*, *90*, 247–251. doi:10.1002/j.2168-9830.2001.tb00599.x

Porter, S. R., & Whitcomb, M. E. (2003). The impact of contact type on web survey response rates. *Public Opinion Quarterly, 67,* 579-588. doi:10.1086/378964

Preacher, K. J., Zhang, G., Kim, C., & Mels, G. (2013). Choosing the optimal number of factors in exploratory factor analysis: A model selection perspective. *Multivariate Behavioral Research, 48,* 28-56. doi:10.1080/00273171.2012.710386

Purzer, S. (2011). The relationship between team discourse, self-efficacy, and individual achievement: A sequential mixed-methods study. *Journal of Engineering Education, 100,* 655-679. doi:10.1002/j.2168-9830.2011.tb00031.x

Reisberg, R., Bailey, M., Burger, C., Hamann, J., Raelin, J., & Whitman, D. (2010). The effect of gender on support and self-efficacy in undergraduuate engineering programs. *Proceedings of the American Society for Engineering Education 2010 Annual Conference and Exhibition,* Lousiville, Kentucky.

Schaefers, K. G., Epperson, D. L., & Nauta, M. M. (1997). Women's career development: Can theoretically derived variables predict persistence in engineering majors? *Journal of Counseling Psychology*, *44*, 173–183. doi:10.1037/0022-0167.44.2.173

Schreuders, P. D., Mannon, S. E., & Rutherford, B. (2009). Pipeline or personal preference: women in engineering. *European Journal of Engineering Education*, *34*, 97–112. doi:10.1080/03043790902721488

Schubert, T. F., Jacobitz, F. G., & Kim, E. M. (2012). Student perceptions and learning of the engineering design process: an assessment at the freshmen level. *Research in Engineering Design*, *23*, 177–190. doi:10.1007/s00163-011-0121-x

Schunk, D. H. (1982). Effects of effort attributional feedback on children's perceived self-efficacy and achievement. *Journal of Educational Psychology, 74,* 548-556. Retrieved from http://libres.uncg.edu/ir/uncg/f/D_Schunk_Effects_1982.pdf

Schunk, D. H., & Pajares, F. (2002). The development of academic self-efficacy. In A. Wigfield & J. Eccles (Eds.), *Development of achievement motivation* (pp. 16-31). San Diego: Academic Press.

Schunk, D. H., & Pajares, F. (2005). Competence perceptions and academic functioning. In A. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 85-104). New York: The Guilford Press.

Schwarzer, R., & Jerusalem, M. (1995). Generalized self-efficacy scale. In J. Weinman, S. Wright, & M. Johnston, (Eds.) *Measures in health psychology: A user's portfolio. Causal and control beliefs* (pp. 35-37). Windsor, UK: Nfer-Nelson.

Seltman, H. J. (2013). *Experimental Design and Analysis.* Retrieved from http://www.stat.cmu.edu/~hseltman/309/Book/Book.pdf

Sheehan, K. B. (2001). E-mail survey response rates: A review. *Journal of Computer-Medicated Communication,6*(2). Online publication. doi:10.1111/j.1083-6101.2001.tb00117.x

Shivy, V. A., & Sullivan, T. N. (2005) Engineering students' perceptions of engineering specialties. *Journal of Vocational Behavior, 67,* 87-101. doi:10.1016/j.jvb.2003.05.001

Stevens, J. P. (2002). *Applied multivariate statistics for the social sciences* (4th ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Su, R., Rounds, J., & Armstrong, P. I. (2009). Men and things, women and people: A meta-analysis of sex differences in interests. *Psychological Bulletin, 135,* 859-884. doi:10.1037/a0017364

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Upper Saddle River, NJ: Pearson.

Thompson, B. (2004). *Exploratory and confirmatory factor analysis.* Washington, DC: American Psychological Association.

Towle, E., Mann, J., Kinsey, B., O'Brien, E. J., Bauer, C. F., & Champoux, R. (2005). Assessing the self-efficacy and spatial ability of engineering students from multiple disciplines. *Proceedings Frontiers in Education 35th Annual Conference*. Indianapolis: IEEE. doi:10.1109/FIE.2005.1612216

Veenstra, C. P. , Dey, E. L., & Herrin, G. D. (2008). Is modeling of freshman engineering success different from modeling of non-engineering success? *Journal of Engineering Education, 97,* 467-479. doi:10.1002/j.2168-9830.2008.tb00993.x

Veenstra, C. P., & Herrin, G. D. (2006). Using the SAT and ACT scores for placement into engineering freshman courses. *Proceedings of the 119th American Society of Engineering Education Conference, Chicago, Illinois.*

Vogt, C. (2003). An account of women's progress in engineering: A social cognitive perspective. *Journal of Women and Minorities in Science and Engineering*, *9*, 217–238. doi:10.1615/JWomenMinorScienEng.v9.i34

Vogt, C. (2008). Faculty as a critical juncture in student retention and performance in engineering programs. *Journal of Engineering Education*, *97*(1), 27–36. doi:10.1002/j.2168-9830.2008.tb00951.x

Vogt, C. M., Hocevar, D., & Hagedorn, L. S. (2007). A social cognitive construct validation: Determining women’s and men's success in engineering programs. *The Journal of Higher Education*, *78*, 337–364. doi:10.1353/jhe.2007.0019

Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology*, *25*, 68–81. doi:10.1006/ceps.1999.1015

Wigfield, A., & Eccles, J. S. (2002). The development of competence beliefs and values from childhood through adolescence. In A. Wigfield & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 92-120). San Diego: Academic Press.

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist, 34,* 806-838. doi:10.1177/0011000006288127

Yoder, B. L. (2011). *Engineering by the numbers.* Retrieved from http://www.asee.org/papers-and-publications/publications/college-profiles/2011-profile-engineering-statistics.pdf

Zeldin, A. L., & Pajares, F. (2000). Against the odds: Self-efficacy beliefs of women in mathematical, scientific, and technological careers. *American Educational Research Journal, 37*, 215-246. doi:10.3102/00028312037001215

Zhang, G., Anderson, T. J., Ohland, M. W., Carter, R., & Thorndyke, B. R. (2004). Identifying factors influencing engineering student graduation: A longitudinal and cross-institutional study. *Journal of Engineering Education, 93,* 313-320. doi:10.1002/j.2168-9830.2004.tb00820.x

Vita

NATASHA JOHANNA A. MAMARIL
Spring 2014

EDUCATION

Master of Science, **Educational Psychology**
Department of Educational, School, and Counseling Psychology, University of Kentucky. Master's Thesis: *Through the Pipeline: A Qualitative Study of Women's Self-Beliefs in Engineering.* Thesis adviser: Dr. Ellen Usher. May 2009.

Bachelor of Science, **Chemical Engineering**
Department of Chemical Engineering, University of the Philippines Los Baños, College, Laguna, Philippines. Undergraduate Thesis: *Citric Acid Production from Cassava Pulp Using Aspergillus Niger.* Thesis adviser: Dr. Pham Binh Chay. July 1996. Cum Laude. Licensed Chemical Engineer. Board certified May 1997.

PUBLICATIONS

PEER-REVIEWED PROCEEDINGS

Mamaril, N. A., Economy, D. R., Usher, E. L., & Kennedy, M. S. (2013). An examination of students' motivation in engineering service courses. *Proceedings of the 2013 Frontiers in Education Conference, Oklahoma,* 1825-1827. doi:10.1109/FIE.2013.6685152

Gaffney, J. D. H., Housley Gaffney, A. L., Usher, E. L., & Mamaril, N. A. (2013). How an activity-learning class influences physics self-efficacy in pre-service teachers. *Proceedings of the American Institute of Physics 1513*, 134-137. doi:10.1063/1.4789670

TECHNICAL PAPERS

Crabtree, J. D., & Mamaril, N. A. (2008). *Preliminary evaluation of USDOT number readers and license plate readers at Kentucky weigh stations* (KTC-08-27/RSF20-06-1I). Lexington, Kentucky: University of Kentucky, Kentucky Transportation Center.

Crabtree, J. D., Wallace, C. Y., & Mamaril, N. J. (2008). *Technology scan for electronic toll collection* (KTC-08-15/SPR359-08-1F). Lexington, Kentucky: University of Kentucky, Kentucky Transportation Center.

MANUSCRIPTS IN PREPARATION

Mamaril, N. A., Usher, E. L., Economy, D. R., & Kennedy, M. S. (in preparation). *Measuring* u*ndergraduate students' engineering self-efficacy: Assessment and implications.* Status: Empirical study in preparation.

Mamaril, N. A., Usher, E. L., Economy, D. R., & Kennedy, M. S. (in preparation). *Identifying the sources of undergraduate engineering students' self-efficacy.* Status: Data collected and analyzed.

Mamaril, N. A., Usher, E. L., Gaffney, J. D. H., & Housley Gaffney, A. L. (in preparation). *Investigating preservice teachers' physics teaching self-efficacy: A mixed method approach.* Empirical study in preparation.

Mamaril, N. A., & Usher, E. L. (in preparation). *Through the pipeline: A qualitative study of women's self-beliefs in engineering*. Empirical study in preparation.

PRESENTATIONS

Mamaril, N. A., Usher, E. L., Economy, D. R., & Kennedy, M. S. (2014, April). *Measuring undergraduate students' engineering self-efficacy: A scale validation study.* Paper presented at the 2014 Spring Research Conference, Cincinnati, Ohio.

Li, C. R., Conway, A. E., Kim, A., Butz, A. R., **Mamaril, N. A.**, & Usher, E. L. (2014, April). *Sources of academic and self-regulatory self-efficacy of at-risk students in an alternative school environment.* Poster presented at the 2014 Spring Research Conference, Cincinnati, Ohio.

Mamaril, N. A., Usher, E. L., Economy, D. R., & Kennedy, M. S. (2014, April). *Identifying the sources of undergraduate engineering students' self-efficacy.* Poster presented at the annual meeting of the American Educational Research Association, Philadelphia, Pennsylvania.

Mamaril, N. A., Economy, D. R., Usher, E. L., & Kennedy, M. S. (2013, October). *An examination of students' motivation in engineering service courses.* Paper presented at the 43rd Annual Frontiers in Education Conference, Oklahoma City, Oklahoma.

Mamaril, N. A., Maxson, T. T., Cooper, R. E., Turpin, J. A., Usher, E. L., Gaffney, J. D. H., & Housley Gaffney, A. L. (2013, April). *Investigating preservice teachers' physics teaching self-efficacy: A mixed method approach.* Paper presented at the 2013 Spring Research Conference, Lexington, Kentucky.

Presentations (continued)

Mamaril, N. A., Waiters, B. L., Deatrick, E. E., Economy, D. R., Usher, E. L., & Kennedy, M. S. (2013, April). *Sources of undergraduate students' engineering self-efficacy: A qualitative study.* Paper presented at the 2013 Spring Research Conference, Lexington, Kentucky.

Usher, E. L., **Mamaril, N. A.**, Gaffney, J. D. H., & Housley Gaffney, A. L. (2012, April). *Building education majors' confidence for teaching physics.* Poster presented at the annual meeting of the American Educational Research Association, Vancouver, British Columbia, Canada.

Mamaril, N. A., Usher, E. L., & Coyle, B. A. (2012, March). *Academic self-handicapping and self-efficacy as predictors of mathematics achievement of African American middle school students.* Poster presented at the 2012 Spring Research Conference, Louisville, Kentucky.

Mamaril, N. A., Usher, E. L., Gaffney, J. D. H., & Gaffney, A. L. H. (2012, February). *Building education majors' confidence for teaching physics.* Paper presented at the Third Annual University of Kentucky STEM Symposium, Lexington, Kentucky.

Gaffney, J. D. H., **Mamaril, N. A.**, Housley Gaffney, A. L., & Usher, E. L. (2011). *Improving physics self-efficacy in pre-service teachers.* Paper presented at the PERC Annual Conference, Omaha, Nebraska.

Thomas, M. K., Usher, E. L., & **Mamaril, N. A.** (2011, August). *Investigating the relationship between teacher feedback and student self-efficacy.* Poster presented at the 119th American Psychological Association Convention, Washington, D.C.

Mamaril, N. A., Brueggeman, B., Willett, T., Lynch, A., Thomas, M. K., & Usher, E. L. (2011, April). *Investigating the relationship between teacher feedback and student self-efficacy.* Poster presented at the 2011 Spring Research Conference, Cincinnati, Ohio.

Mamaril, N. A., & Usher, E. L. (2010, August). *Through the pipeline: A qualitative study of women's engineering self-efficacy.* Paper presented at the 118th American Psychological Association Annual Convention, San Diego, California.

Mamaril, N. A. (2010, April). *Development and validation of an engineering self-efficacy scale for college students.* Paper presented at the Spring Research Conference, Lexington, Kentucky.

Mamaril, N. A. (2009, October). *The plight of African American students in engineering programs.* Paper presented at the Mid-Western Educational Research Association (MWERA) Annual Meeting, Sheraton Westport Chalet, St. Louis, Missouri.

Presentations (continued)

Mamaril, N. J. A. (2009, April). *Through the pipeline: A qualitative study of women's self-beliefs in engineering.* Paper presented at the Spring Research Conference, University of Louisville, Kentucky.

Mamaril, N. J., & Royal, K. D. (2008, October). *Women and minorities in engineering: A review of the literature.* Paper presented at the Mid-Western Educational Research Association (MWERA) Annual Meeting, Westin Great Southern Hotel, Columbus, Ohio.

FUNDED RESEARCH

Project Manager and Research Assistant — September 1, 2012 – June 6, 2014
Collaborative Research: Research Initiation Grant: Influence of Motivation on Learning Outcomes in an Engineering Service Course
National Science Foundation, Research Initiation Grant in Engineering Education (RIGEE) (EEC Award No. 1240328)
Principal investigators: Dr. Ellen L. Usher (University of Kentucky) and Dr. Marian Kennedy (Clemson University)
$150,000
Status: Funded September 1, 2012

International Fellowship — Fall 2008 – Spring 2009
Through the Pipeline: A Qualitative Study of Women's Self-Beliefs in Engineering (M.S. Thesis)
American Association of University Women (AAUW)
$18,000

ADDITIONAL RESEARCH EXPERIENCE

Research Assistant, P20 Motivation and Learning Lab, — Fall 2012 – Spring 2014
University of Kentucky
Supervisor: Dr. Ellen Usher, Director

Research Team Member, **P20 Motivation and Learning Lab,** — Fall 2010 – Spring 2012
University of Kentucky
Supervisor: Dr. Ellen Usher, Director

Graduate Assistant, Institutional Research, Planning, and Effectiveness, University of Kentucky — Spring 2008 – Summer 2012
Supervisor: Tara Rose, Director of Assessment

Additional Research Experience (continued)

Graduate Assistant, College of Health Sciences, Spring 2012
University of Kentucky
Supervisor: Dr. Sharon Stewart, Interim Dean

Research Assistant, Intelligent Transportation Systems, Kentucky Transportation Center, College of Engineering, Fall 2007, Summer 2008
University of Kentucky
Supervisor: Dr. Joseph Crabtree, Director

Technical Services and Applications Development Engineer, Technical Department, 3M Philippines October 1997 – January 2006
Philippines
Supervisor: Andy Juan, Manager

Research Assistant, National Institute of Molecular Biology and Biotechnology, 1995 – 1996
University of the Philippines
Supervisor: Dr. Pham Binh Chay, Project Leader

AWARDS AND RECOGNITION

Doctoral Research Seminar, American Psychological Association, Division 15, Fall 2011.
American Association of University Women International Fellowship, 2008 - 2009.
Pathfinder Award for Epoxy Coating for Aluminum-Titanium-Carbon Jigs, 3M International, 2006.
Technical Employee of the Year, 3M Philippines, Inc., 2003.
Best Six Sigma Growth Project, 3M Philippines, Inc., 2003.
Award for Scholastic Achievement, International Honor Society of Phi Kappa Phi, 1997.
Award for Scholastic Achievement and Recipient of Chancellor's Pin for graduating *cum laude* from the University of the Philippines, 1996.

COLLEGE TEACHING EXPERIENCE

Fall 2010 Introduction to Educational Psychology (EDP 548), University of Kentucky, Teaching Assistant.

PREVIOUS WORK EXPERIENCE

2005 - 2006 3M Philippines, Inc.
Technical Supervisor

2004 - 2005 3M Philippines, Inc., Electronics Markets Material Division
Applications Development Engineer/Technical Marketing

Previous Work Experience (continued)

2002 - 2003	3M Philippines, Inc., Industrial Adhesives and Tapes Division Applications Development Engineer
2000 - 2002	3M Philippines, Inc., Industrial Adhesives and Tapes Division Advanced Technical Services Engineer
1997 - 2000	3M Philippines, Inc., Industrial Tapes and Specialties Division Technical Services Engineer
1996 - 1997	Novartis Pharmaceuticals, Philippines Technical Assistant for Production